Improved Tuna Swarm-based U-EfficientNet: Skin Lesion Image Segmentation by Improved Tuna Swarm Optimization

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***Abstract*—Skin cancers have been on an upward trend, with melanoma being the most severe type. A growing body of investigation is employing digital camera images to computer-aided examine suspected skin lesions for cancer. Due to the presence of distracting elements including lighting fluctuations and surface light reflections, interpretation of these images is typically difficult. Segmenting the area of the lesion from healthy skin is a crucial step in the diagnosis of cancer. Hence, in this research an optimized deep learning approach is introduced for the skin lesion segmentation. For this, the EfficientNet is integrated with the UNet for enhancing the segmentation accuracy. Also, the Improved Tuna Swarm Optimization (ITSO) is utilized for adjusting the modifiable parameters of the U-EfficientNet to minimize the information loss during the learning phase. The proposed ITSU-EfficientNet is assessed based on various evaluation measures like Accuracy, Mean Square Error (MSE), Precision, Recall, IoU, and Dice Coefficient and acquired the values are 0.94, 0.06, 0.94, 0.94, 0.92 and 0.94 respectively.**

Keywords*—*Skin lesion; skin cancer; segmentation; deep learning model; optimization; EfficientNet; UNet

I. INTRODUCTION

The most prevalent fatal disease with the fastest rate of growth is skin cancer. According to the World Health Organization, melanoma accounts for one out of every three cases of cancer. With five million patients per year, the disease is the most widely recognized type of cancer in the United States [1]. Timely skin cancer detection contributes to better health care delivery. As melanocytes multiply indiscriminately, very first trace of hyper-pigmentation appears. Melanoma is the term used to describe this type of skin cancer. Around 9000 people die from cancer each year in the world, making it the deadliest kind [2]. In people suffering from advanced melanoma, the survival rate after beyond five years is 95%, whereas in those with early melanoma, the mortality rate is 1.62%. The importance of early detection, treatment, and recovery can indeed be emphasized in the case of melanoma [3].

Microscopic (Dermoscopic) and macroscopic (clinical) images are the two imaging modalities most frequently used in advanced skin lesion diagnosis [4]. Although dermatologists sometimes lack access to dermoscopic images that are enabled by the examination of lesion characteristics that are imperceptible to the bare eye. Conversely, whereas they are more readily available, clinical photographs taken with traditional cameras have lesser quality [5,6]. Dermoscopy is a non-invasive skin imaging method that helps dermatologists diagnose skin lesions by enabling them to see beyond the skin's surface. Nonetheless, based on the clinician's knowledge and expertise, the prognostic value of dermoscopy might vary significantly, from 24% to 77% [7]. In addition, when used by untrained dermatologists, dermoscopy may actually reduce detection ability. Thus, it is essential to develop Computer-Aided Diagnosis (CAD) systems in order to minimize diagnosis mistakes brought on by the challenging nature of visual assessment, the subjectivity involved, and to lessen the burden of skin illnesses and the inaccessibility of dermatologists [8, 9].

By evaluating clinical images, CAD is a significant equivalent that aids healthcare practitioners in their everyday treatment diagnostic. For computer vision tasks, deep learning (DL) has provided a strong basis, and Designs aren't an exception [10]. Dermoscopic images can potentially be stored and retrieved on processors using the digitized dermoscopic devices that are already accessible [11]. CAD systems would aid less-experienced dermatologists and have a lesser impact for inter-subject variation because dermoscopy diagnosis reliability is always demonstrated to rely upon the knowledge of the dermatologist. The conventional method for automatic dermoscopic image assessment typically involves the following phases: lesion categorization, extraction of features, and segmentation of image [12, 13]. Since precision constitutes one of segmentation's primary qualities, it is considered as the most crucial stages in diagnosing the skin cancer [14]. Segmentation is challenging, though, due to the wide range of lesion colors, sizes, and types, as well as the various skin types and textures [15].

The separation of an image into useful areas is known as segmentation. In instance, segmentation classifies the essential area with the proper classes and labels [16]. Here, the approach utilized for skin lesions is binary task, i.e., differentiating the tumor from the skin surrounding. Contrast and Lighting problems, occlusions, artefacts, inherent intra-class variability and inter-class similarities, and the variety of other imaging issues make automated skin lesion segmentation a difficult task [17, 18]. A further issue that prevents both the training of models and the accurate evaluation of those models is the unavailability of big datasets with expert-generated ground-truth segmentation masks [19]. The segmentation of skin lesions can be divided into four categories: deep learning approaches, conventional intelligence-based approaches, edge and region-based approaches and threshold and clustering-based approaches [20]. Each class's benefits and drawbacks were noted. Deep learning approaches also outperform traditional approaches in the analysis of complicated issues [21]. To analyze medical images, there are many different analytical methods. Yet, in recent years, there have been notable improvements in computer hardware and software systems as well as a sharp rise in the volume and complexity of data [22]. Deep learning techniques for precise and accurate medical image analysis have proliferated and improved as a result of these breakthroughs [23].

The first effort to apply convolutional layers in the task of segmenting disease diagnosis was made in the previous ten years [24]. Following that, a number of designs were put forth to improve segmentation accuracy, not just in the healthcare profession but in general. Such designs included Fully Convolutional Network (FCN), FC-DenseNet, and U-Net for segmenting clinical data [25]. Several structures improved image segmentation for images from the medical area, for example. In terms of State of the Arts (SOTA) efficiency, the encoder-decoder and skip links network U-Net has excelled in the segmentation of medical images [26]. To that purpose, several adaptations have been introduced for diverse clinical uses using better image sources. Such approaches share a similar flaw in that they are unable to accurately localize feature representations for monotone segmentation outcomes by capturing long-range contextual data. Due to the convolution layers' constrained receptive field, this flaw results from the Convolutional Neural Network (CNN) weakness [27]. In the medical area, where precise separation of tissue and organ boundaries areas is required, the degradation of conceptual localization information over the levels is not the preferred outcome for semantic segmentation [28][39-43]. A novel framework must therefore be created employing a deep learning architecture in order to achieve the higher efficiency in the segmentation algorithm.

Hence, the goal of the research is to devise a novel deep learning strategy for segmenting the skin lesion with enhanced accuracy for detecting the cancer more effectively in the future. The artefact removal along with the optimized hybrid deep learning approach is utilized for performing the segmentation. The major contributions of the research are:

- ***Design of ITSO Algorithm***: The Improved Tuna Swarm Optimization (ITSO) algorithm is designed by integrating the TSO with the effective solution updating behaviour of the Pelican for enhancing the convergence rate and to eliminate the movement of solution away from the optimal region.
- ***Design of ITSU-EfficientNet***: The ITSU-EfficientNet is designed by integrating the EfficientNet and the UNet, wherein the encoder part of the UNet is replaced with the EfficientNet for enhancing the segmentation accuracy. Besides, the adjustable parameters of the hybrid deep learning model are tuned using the ITSO algorithm to reduce the information loss during the information learning phase.

The organizations of the research are: Section II details the literature review along with the problem statement. The proposed skin lesion segmentation is detailed in Section III and the experimental outcome with its interpretation is provided in Section IV and Section V concludes the work.

II. RELATED WORK

Skin lesion segmentation using the semi-supervised learning was designed by [29], wherein the hybrid Transformer encoders and CNN were combined to acquire the global and local attributes. The designed model was most suited for solving the challenges like over fitting and un-stability. In this, the semantic attributes were learned by the semi supervised model that enhances the learning capability of the model. The devised model accomplished superior performance compared to the traditional methods of skin lesion segmentation. Still, the performance gets degraded due to the noisy annotation criteria while enriching the data sample.

A hybrid deep learning approach for skin lesion segmentation was devised by [30], wherein the ResNet and AlexNet were combined together for enhancing the segmentation accuracy. Initially, the color constancy of the image was enhanced through the pre-processing stage using the gray world algorithm. Also, the resizing was also devised for making the input more appropriate to the segmentation module. Here, the loss functions like Tversky loss function and cross entropy were considered minimizing the loss during the lesion segmentation. The devised model accomplished superior performance in terms of segmentation accuracy with minimal computation overhead. Still, the image with low contrast and color variations affects the performance of the model.

Skin lesion segmentation using the Grab cut approach was devised by [31], wherein the skin hair removal and corner borders removal were devised in the image pre-processing for enhancing the performance of the model. In the hair removal task, the detection of hair contour was devised and then the mask was generated for removing the hair from the input image. After removing the hair, the contrast was improved through the equalization strategy. Finally, the segmentation was performed using the Grab cut approach and accomplished better performance in terms of Dice and Jaccard coefficients. However, the method was not applicable for segmenting small lesion.

The lesion segmentation using the deep learning was designed by [32] for enhancing the accuracy of segmentation. In this method, the hair in the image was removed through the morphological filters and inpainting algorithms. Followed by, the data augmentation was devised for enriching the database, because the classifier learned with larger amount of data elevates the generalization capability that enhances the detection accuracy. The augmented image is fed into the hybrid deep learning model designed by combining ResNet and UNet. The enhanced performance was acquired by the model based on the assessment measures like the recall and precision. Besides, the post-processing was utilized in the model for enhancing the accuracy of model. Still, the issues like under and over segmentation may occur while evaluating the performance using larger data.

Skin lesion segmentation using the metaheuristic approach was designed by [33] through a hybrid optimization strategy. In this, differential evolution and the artificial bee colony algorithms were combined together for performing the segmentation task. Here, the entropy, intensity values and the number of edge pixels were considered for the evaluation of the objective function. The designed model accomplished superior performance compared to the conventional methods. Still, the requirement of the additional sharpening and smoothening approaches enhances the noise that in turn degrades the performance of the model.

A. Motivation and Problem Statement

The first stage in computerized dermoscopic image processing is effectively separating the tumor from the skin that surrounds it. The fact that melanoma typically has a wide range of physical attributes in terms of color, shape, and size, as well as various textures and skin types, makes the process challenging. The difference in brightness among the lesion and the surrounding skin can also vary, with some lesions having fuzzy and uneven edges. In a variety of medical imaging applications and pattern recognition, deep learning techniques recently demonstrated encouraging results. Hence, in this research, an automatic skin lesion segmentation based on deep learning is introduced to overcome the above-mentioned challenges. The initial pre-processing stage removes the artefacts from the image. Followed by, the optimized hybrid deep learning approach enhances the detection accuracy with minimal computation burden.

III. METHODOLOGY

The skin lesion segmentation is utilized for the detection and classification of the cancer to identify the severity of the disease. The more accurate detection of the disease is employed through the efficient segmentation approach. Deep learning technique is widely utilized in image processing any several other computer vision applications due to the promising outcome. Hence, in this research skin lesion detection is devised using the deep learning approach. For this, improved tuna swarm optimization based UNet-EfficientNet (ITSU-EfficientNet) is introduced. In this, the input skin image is taken from the dataset and is initially pre-processed using the median filtering for the removal of artefacts from the image. Followed by, the skin segmentation is devised using the novel U-EfficientNet, which is designed by integrating the UNet and EfficientNet. Here, the optimal parameters of the classifier are tuned using the proposed ITSO algorithm. It is designed by integrating the TSO with the effective solution updating strategy of the Pelican optimization algorithm.

The introduced ITSO algorithm has the balanced exploration and exploitation phases for obtaining the global best solution. The workflow of the proposed ITSU-EfficientNet is depicted in Fig. 1.

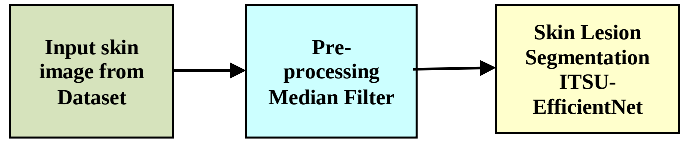

Fig. 1. Block diagram of proposed ITSU-EfficientNet for skin lesion segmentation.

A. Image Acquisition

The input skin is acquired from the publicly available dataset, wherein the dataset N comprises of n number of images, wherein N_i^{th} image is taken for processing the proposed method. It is represented as,

$$N = \{N_1, N_2, ...N_i, ...N_n\} \tag{1}$$

B. Removing Artefacts

To eliminate noise and artefacts from the input image acquired from the patient, image pre-processing is devised. The median filtering technique is used in this instance of the suggested work for image pre-processing. The clean composites that aid in removing noise are produced by computing the median value for each pixel in the image. Thus, the image produced after the pre-processing is represented as P_s , which is fed into the segmentation module.

C. Skin Lesion Segmentation using ITSU-EfficientNet

The artefact removed image is fed into the proposed ITSU-EfficientNet for segmenting the skin lesion. In this, the UNet and EfficientNet are integrated together and the adjustable parameters like the weights and bias are tuned using the improved ITSO algorithm. The detailed description is given below.

1) *Architecture of UNet:* Lightweight features, feature map fusion, and Local receptive field are common characteristics of deep learning models including UNet. The over fitting issues of the deep learning models are minimized through the parallel structure that makes the computation simpler and more flexible. Contrary to a full convolutional neural network (FCN), the significant characteristics like the feature mapping based on splicing criteria and the structure of the skip connection makes the UNet simpler with minimal computation overhead. According to Fig. 2, the midway link between up and down sampling adds low-level attributes to the final process, which minimizes the losses of beneficial properties in skin lesion segmentation [34].

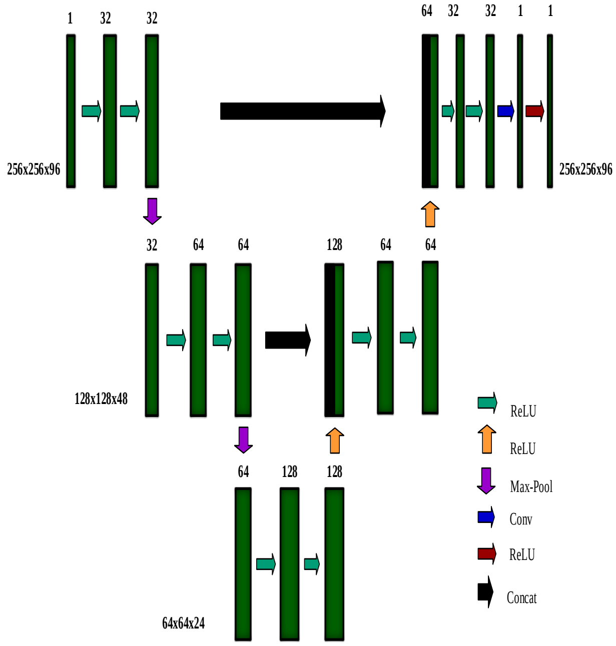

Fig. 2. Architecture of UNet.

In UNet, skip connection, down sampling (pooling), up sampling, and convolution techniques are widely employed. Max pooling is a popular down sampling approach that is used to get abstract features and high-level features with an emphasis on the semantic content of images while reducing image resolution. Common up-sampling methods include regular forward propagation backwards and de-convolution without gradient updating. It is possible to define UNet's in the field of image segmentation for enhancing the detection accuracy.

2) Architecture of EfficientNet: EfficientNet-v2 for the estimation of the loss function utilizes smaller kernel sizes of 3×3 with minimal memory access overhead. Besides, the last stride-1 is eliminated for the reduction of the memory access overhead and size of parameter. The runtime overhead is minimized through network capacity elevation and the training overhead along with higher memory are minimized by restricting the interference of image. The learning capability of the EfficientNet-v2is higher by making original interference size for learning that depicts the scaling characteristics of the loss function estimator [35]. The building blocks of the EfficientNet-v2 are fused MBConv long with the mobile inverted bottleneck MBConv and are portrayed in Fig. 3.

The resolution, depth and width of the network are balanced by the EfficientNet-v2 to enhance the accuracy of skin lesion segmentation. Here, the compound coefficient η is utilized for the scaling the network parameters and is expressed as,

$$resolution = \mu^{\eta}; \quad depth = \beta^{\eta}; \quad width = \chi^{\eta} \tag{2}$$

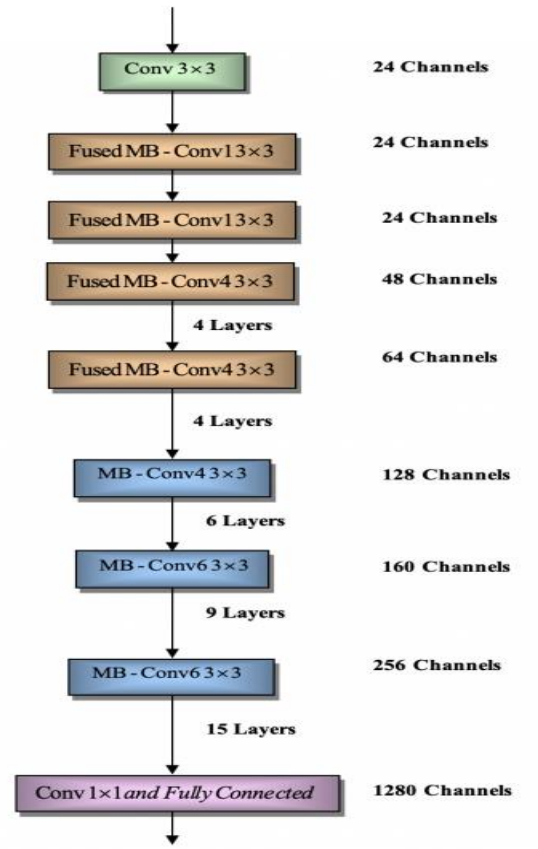

Fig. 3. Architecture of EfficientNet-v2.

where,

$$\beta^2.\chi^2.\mu \approx 2$$
$$\beta, \chi, \mu \geq 1 \tag{3}$$

Here, the factors β, χ, μ decides the distribution of the external resources in the network and η refers to the coefficient that is identified based on β, χ, μ.

D. Proposed ITSU-EfficientNet based Skin Lesion Segmentation

The skin lesion segmentation using the proposed ITSU-EfficientNet is designed by hybridizing the UNet and EfficientNet as shown in Fig. 4, wherein the ITSO is utilized for tuning the adjustable parameters. UNet architecture is comprised of two parts, encoder and decoder. In the proposed model UNet encoder is replaced by EfficientNet B7 and decoder is similar as UNet decoder. UNet decoder comprises of block of 3x3 conv and feature maps are

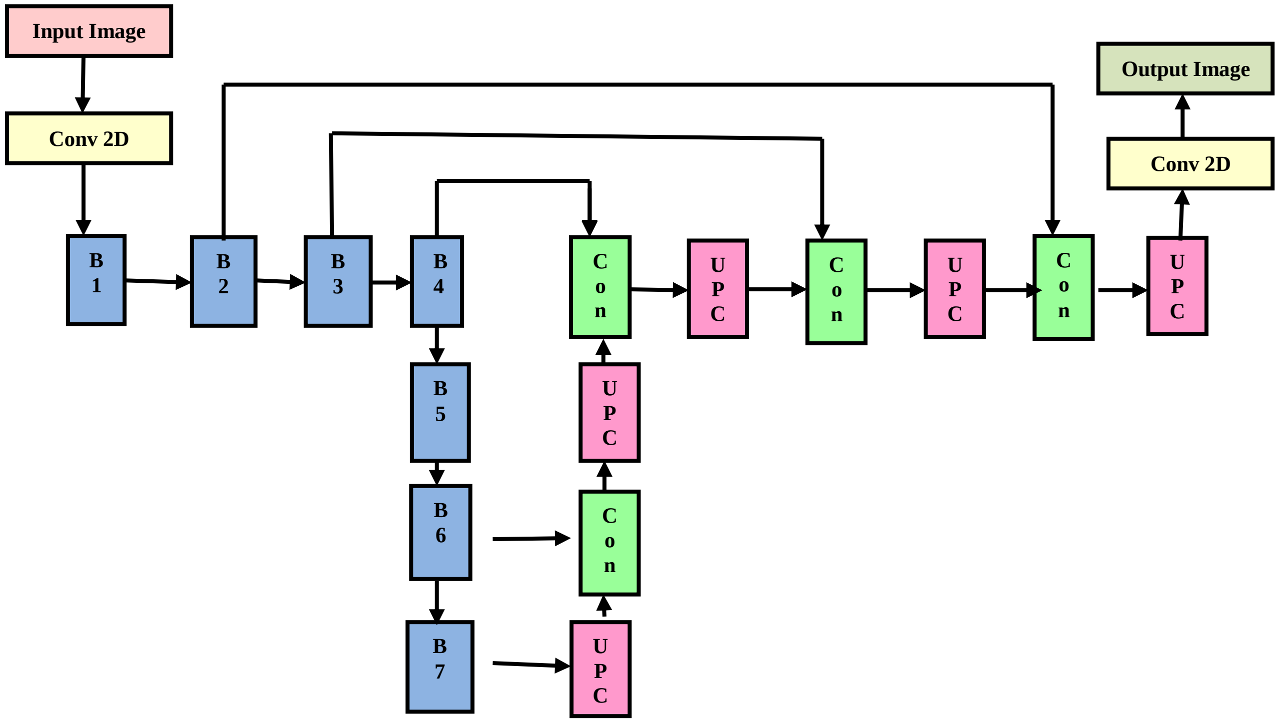

Fig. 4. Architecture of proposed U-EfficientNet.

unsampled after each block and concatenate the features from encoder and forward them to next block of 3x3 convolutions. After last block a 1x1 conv is used to generate segmentation map.

1) Improved Tuna Swarm Optimization (ITSO): A metaheuristic algorithm with the balanced diversification and intensification helps to obtain the global best solution for solving the optimization issues. The Tuna Swarm Optimization (TSO) is the one that has the balanced diversification and intensification, which designed based on the marine predator named Tuna. This marine predator follows the fishtail shape swimming behaviour that is unique and faster in a continuous manner. Still, the swimming capability of the predator is very slower compared to the small nimble fish. The marine predator follows the swarm behaviour for capturing the prey (target). Hence it uses two various approaches for capturing the target fish.

- ***Spiral Diving***: The swarm of tuna follows the spiral diving approach to capture the prey intending it (prey) to move towards the swallow water. This strategy helps to capture the target more easily.
- ***Parabolic Structure***: The second approach of the tuna in capturing the target is the parabolic structure formation. In this, the tuna of swarm forms the parabolic structure one after another for encircling the prey and capture it.

2) Mathematical Modelling: The mathematical modelling of the ITSO comprises of three various steps like initialization, diversification and intensification. Here, initialization is nothing but the initialization of candidates (Tuna) and target in the feature space. The second step is the diversification phase, wherein the candidates explore the feature space for the acquisition of *global* best solution. For this, the spiral diving strategy is utilized by the candidates in the feature space. Finally, the intensification phase is devised for deeply exploiting the feature space that is already identified in the diversification phase [36]. Here, the movement of solution away from the optimal location is minimized by incorporating the effective solution updating behaviour of the Pelican in the Pelican optimization algorithm [37]. The capturing of the target is the solution accomplished by the algorithm for tuning the optimal parameters of the lesion segmentation technique.

Initialization: In the feature space, the candidates are located randomly and is represented as,

$$S_m^\tau = k \cdot (U - V) + V \ , m = 1,2,\ldots Z \tag{4}$$

where, the lower and upper boundaries of the feature space is notated as V *and* U respectively and the random number chosen from the uniform distribution in the range of $[0,1]$ is indicated as k, and the m^{th} candidate in the feature space at the iteration τ is indicated as S_m^τ.

Fitness Estimation: After initializing the candidates in the feature space, the fitness is estimated based on mean square error and is formulated as,

$$F_{ITSO} = \frac{1}{T_{sol}} \sum_{i=1}^{T_{sol}} (SS_{obser} - SS_{tar})^2 \tag{5}$$

where, the fitness of the solution is referred as F_{ITSO}, the total count of samples is indicated as T_{sol}, the observed solution is indicated as SS_{obser} and the target solution is indicated as SS_{tar}.

Diversification: In the diversification phase, the spiral diving-based foraging is devised by the candidates for capturing the target. The prey tries to escape from the candidate by changing the direction of swimming. Thus, the candidates form the tight spiral to capture the prey and hence the escaping capability of the prey gets reduced. In addition, the information sharing among the candidates helps to explore more area in the feature space. The position updating of the candidates in the diversification phase is formulated as,

$$S_m^{\tau+1} = \begin{cases} \delta_1 \cdot \left(S_G^\tau + \gamma \cdot \left| S_G^\tau - S_m^\tau \right| \right) + \delta_2 \cdot S_m^\tau, & m = 1 \\ \delta_1 \cdot \left(S_G^\tau + \gamma \cdot \left| S_G^\tau - S_m^\tau \right| \right) + \delta_2 \cdot S_{m-1}^\tau, & m = 2,3,\ldots Z \end{cases} \tag{6}$$

$$\delta_1 = q + (1-q) \cdot \frac{\tau}{\tau^{\max}} \tag{7}$$

$$\delta_2 = (1-q) - (1-q) \cdot \frac{\tau}{\tau^{\max}} \tag{8}$$

$$\gamma = e^{pn} \cdot \cos(2\pi p) \tag{9}$$

$$n = e^{3\cos\left(\left(\left(\tau^{\max} + 1/\tau\right) - 1\right)\pi\right)} \tag{10}$$

where, at $\tau + 1^{th}$ iteration, the position of the m^{th} candidate in the features space is indicated as $S_m^{\tau+1}$, the optimal best candidate in the τ^{th} iteration is indicated as S_G^τ, the movement of the individual candidate in the feature space is controlled by the weight coefficients δ_1 and δ_2, wherein the movement extend is decided by the constant q. The random number that has the range $[0,1]$ is indicated as p and the maximal number of iterations is indicated as $\tau^{\max}$.

When the optimal candidate failed to capture the target; then, the random candidate is chosen from the swarm and hence the exploration criteria is enhanced and the position updating is formulated as,

$$S_m^{\tau+1} = \begin{cases} \delta_1 \cdot \left(S_k^\tau + \gamma \cdot \left| S_k^\tau - S_m^\tau \right| \right) + \delta_2 \cdot S_m^\tau, & m = 1 \\ \delta_1 \cdot \left(S_k^\tau + \gamma \cdot \left| S_k^\tau - S_m^\tau \right| \right) + \delta_2 \cdot S_{m-1}^\tau, & m = 2,3,\ldots Z \end{cases} \tag{11}$$

where, the randomly chosen candidate is indicated as S_k^τ. Here, the efficient position updating behaviour of the Pelican optimization is hybridized with the position updation of the TSO for avoiding the solution escaping from the optimal solution. The solution updation based on the ITSO is formulated as,

$$S_m(\tau) = \begin{cases} S_i(\tau+1) & F_{ITSO}(\tau) < F_{ITSO}(\tau+1) \\ S_i(\tau+1) & Otherwise \end{cases} \tag{12}$$

Thus, the solution updated by the candidates using the effective solution updating criteria guides the solution towards the optimal location that enhances the convergence rate of the algorithm.

Transition Phase: After identifying the target in the feature space, the candidate's moves from the diversification to intensification phase for capturing the target. The formulation for the transition phase is expressed as,

$$S_m^{\tau+1} = \begin{cases} \delta_1 \cdot \left(S_k^\tau + \gamma \cdot \left| S_k^\tau - S_m^\tau \right| \right) + \delta_2 \cdot S_m^\tau, \quad m = 1 & \\ \delta_1 \cdot \left(S_k^\tau + \gamma \cdot \left| S_k^\tau - S_m^\tau \right| \right) + \delta_2 \cdot S_{m-1}^\tau, \quad m = 2,3,\ldots Z & if\ k < \frac{\tau}{\tau^{\max}} \\ \delta_1 \cdot \left(S_G^\tau + \gamma \cdot \left| S_G^\tau - S_m^\tau \right| \right) + \delta_2 \cdot S_m^\tau, \quad m = 1 & \\ \delta_1 \cdot \left(S_G^\tau + \gamma \cdot \left| S_G^\tau - S_m^\tau \right| \right) + \delta_2 \cdot S_{m-1}^\tau, \quad m = 2,3,\ldots Z & if\ k \geq \frac{\tau}{\tau^{\max}} \end{cases} \tag{13}$$

Intensification: In the intensification phase, the parabolic structure-based capturing is devised by the candidates. Here, the target is considered as the point of reference and the parabolic structure is formed. The expression for the intensification-based position updation is defined as,

$$S_m^{\tau+1} = \begin{cases} S_G^\tau + k \cdot \left(S_G^\tau - S_m^\tau \right) + M.a^2 \cdot \left(S_G^\tau - S_m^\tau \right), & if\ k < 0.5 \\ M.a^2 \cdot S_m^\tau, & if\ k \geq 0.5 \end{cases} \tag{14}$$

$$a = \left(1 - \frac{\tau}{\tau^{\max}} \right)^{\left(\tau / \tau^{\max} \right)} \tag{15}$$

where, the random number with the range $[-1,1]$ is indicated as M. Here, also the effective solution updating behaviour of the Pelican is utilized and is expressed as,

$$S_m(\tau) = \begin{cases} S_i(\tau+1) & F_{ITSO}(\tau) < F_{ITSO}(\tau+1) \\ S_i(\tau+1) & Otherwise \end{cases} \tag{16}$$

Thus, the solution acquired by the candidate in the search space through the effective solution updating criteria provides the solution for solving the optimization issues.

Re-estimation of fitness: The feasibility of the solution obtained in the previous phase is estimated by re-estimating the fitness presented in equation (5).

Termination: The acquisition of global best solution or the attainment of $\tau^{\max}$ the iteration of algorithm gets terminated. Pseudo-code for ITSO algorithm is presented in Algorithm 1.

Algorithm 1: Pseudo-code for ITSO algorithm
Input: The values $\tau^{\max}$ and Z are initialized
Output: Best solution S_G^{τ}
Locate the candidates in the feature space $S_m(m=1,2,\ldots Z)$
The factor q is defined
while $(\tau < \tau^{\max})$
Estimate the fitness
Update S_G^{τ}
For (all candidates) do
Update δ_1, δ_2 *and a*
Update the candidate solution using equation (11)
Update the candidate solution using equation (12)
Update the candidate solution using equation (13)
Update the candidate solution using equation (16)
End for
$\tau = \tau ++$
End while
Return the best solution

Thus, the solution updation using the proposed ITSO algorithm elevates the segmentation accuracy with minimal error and fast convergence rate.

E. Experimental Setup

The ITSU-EfficientNet model is implemented using keras framework and backend as Tensorflow 2.1.0. Google colaboratory Pro IDE is used for coding and training. Tesla P100 GPU and 32 GB of RAM is used for our experiments. In all 2594 images, 20% of images are utilized for testing and 80% data is used for training. During experiment, we scaled down the size of images as original image sizes for ISIC 2018 challenge dataset is higher and not uniform. EfficientNet B7 which is trained on ImageNet is used as backbone. Here, mean squared error (MSE) is considered as loss function. Adam optimizer is used as initial optimizer and ITSO is used to further fine tune the weights during training. Model is trained for 200 epochs.

F. Dataset Description

The ISIC 2018 challenge dataset [38] is used for training and testing. The dataset provided by ISIC 2018 challenge is for diagnosing skin lesion. It offers classification task and skin lesion segmentation task. From various clinics and institutions around the world the data was collected. Compared to all publicly available dermoscopic image libraries, ISIC archive is largest one. For skin lesion segmentation, the challenge provides 2594 images with ground truth masks. The image dimensions for segmentation are 2016 × 3024.

IV. Result and Discussion

The experimental outcome along with the comparative analysis of the ITSU-EfficientNet is detailed in this section.

A. Assessment Measures

To measure the performance of proposed model we use following standard metrics. We evaluate model using Dice Coefficient (DC), precision ($\Pr e$), recall (Re), intersection over union (IoU), specificity (Spe) and sensitivity (Sen). These evaluation measures are defined as follows:

$$DC = \frac{2 * SL_{tp}}{2 * SL_{tp} + SL_{fp} + SL_{fn}} \tag{17}$$

$$\Pr e = \frac{SL_{tp}}{SL_{tp} + SL_{fp}} \tag{18}$$

$$\mathrm{Re} = \frac{SL_{tp}}{SL_{tp} + SL_{fn}} \tag{19}$$

$$IoU = \frac{SL_{tp}}{SL_{tp} + SL_{fp} + SL_{fn}} \tag{20}$$

$$Spe = \frac{SL_{tn}}{SL_{tn} + SL_{fp}} \tag{21}$$

$$Sen = \frac{SL_{tp}}{SL_{tp} + SL_{fn}} \tag{22}$$

where, SL_{tp}, SL_{fp}, SL_{tn} and SL_{fn} represents true positive, false positive, true negative and false negative respectively. SL_{tp} denotes correctly segmented lesion pixels, SL_{fp} denotes segmented non-lesion pixels, SL_{tn} denotes un-segmented non-lesion pixels and SL_{fn} denotes un-segmented lesion.

B. Experimental Outcome

The experimental outcome of the ITSU-EfficientNet is depicted in Fig. 5, wherein the skin image acquired from the dataset is depicted in Fig. 5(a), the corresponding ground truth the depicted in Fig. 5(b) and finally, the outcome of the ITSU-EfficientNet is portrayed in Fig. 5(c).

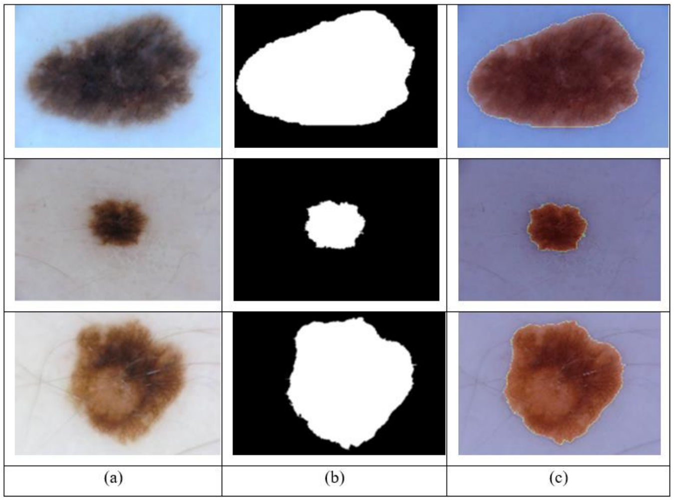

Fig. 5. Experimental outcome (a) Input, (b) Ground truth and (c) segmentation outcome.

C. Performance Assessment

The performance of the ITSU-EfficientNet by varying the epoch is depicted in Fig. 6 based on various assessment measures. In this, the analysis depicts that the higher number of epochs ad the training percentage enhances efficiency of the skin lesion segmentation. The epoch is nothing but the learning cycle utilized by the classifier for performing the skin lesion segmentation for the unknown test image. For example, if the number of epochs utilized by the classifier 40 means, the classifier is trained 40 times with the same data for improving the generalization ability. The outcome of the skin lesion segmentation based on the various assessment measures by varying the epoch interprets that the proposed method accomplished better outcome with maximal epoch of 100.

D. Comparative Assessment

The comparative Assessment of the proposed method with the conventional skin lesion segmentation approaches like ResNet+ UNet [32], ResNet + AlexNet [30], DS-TransUNet [29], and DE-ABC [33]. The assessment based on various evaluation measures is depicted in Fig. 7. Here, with 50 % of data learning, the accuracy estimated by ITSU-EfficientNet is 0.90, which is 9.49%, 9.06%, 2.03%, 1.94%, and 0.36% better than conventional ResNet+UNet, ResNet+AlexNet, DS-TransUNet, and DE-ABC methods. The minimal MSE estimated by ITSU-EfficientNet with 60% data learning is 0.09, which is 35.55%, 33.63%, 18.10%, and 16.09% better than conventional ResNet+UNet, ResNet+AlexNet, DS-TransUNet, and DE-ABC methods. The precision estimated by ITSU-EfficientNet is 0.90 with 70% data learning, which is 6.28%, 5.81%, 2.26%, and 2.06% better than conventional ResNet+UNet, ResNet+AlexNet, DS-TransUNet, and DE-ABC methods. With 80% of data learning the recall evaluatedby ITSU-EfficientNet is 0.92, which is 9.30%, 8.85%, 3.89%, and 1.47% better than conventional ResNet+UNet, ResNet+AlexNet, DS-TransUNet, and DE-ABC methods. The maximal IoU evaluated by ITSU-EfficientNet is 0.92, which is 9.33%, 8.88%, 6.07%, and 1.54% better than conventional ResNet+UNet, ResNet+AlexNet, DS-TransUNet, and DE-ABC methods with 90% of data learning. The maximal Dice coefficient evaluated by ITSU-EfficientNet is 0.90, which is 6.73%, 6.27%, 2.82%, and 1.69% better than conventional ResNet+UNet, ResNet+AlexNet, DS-TransUNet, and DE-ABC methods with 60% of data learning. Here, the proposed method accomplished superior performance compared to the conventional skin care segmentation method. The analysis is devised by varying the training percentage of the proposed model, wherein the performance elevates with increase in training data. The reason behind the enhanced performance is the higher generalization capability of the skin lesion segmentation technique. Also, the optimal adjustment of the hyper-parameters reduces the information loss during the training phase and enhances the outcome of the proposed model. The detailed analysis of the comparative analysis is presented in Table I.

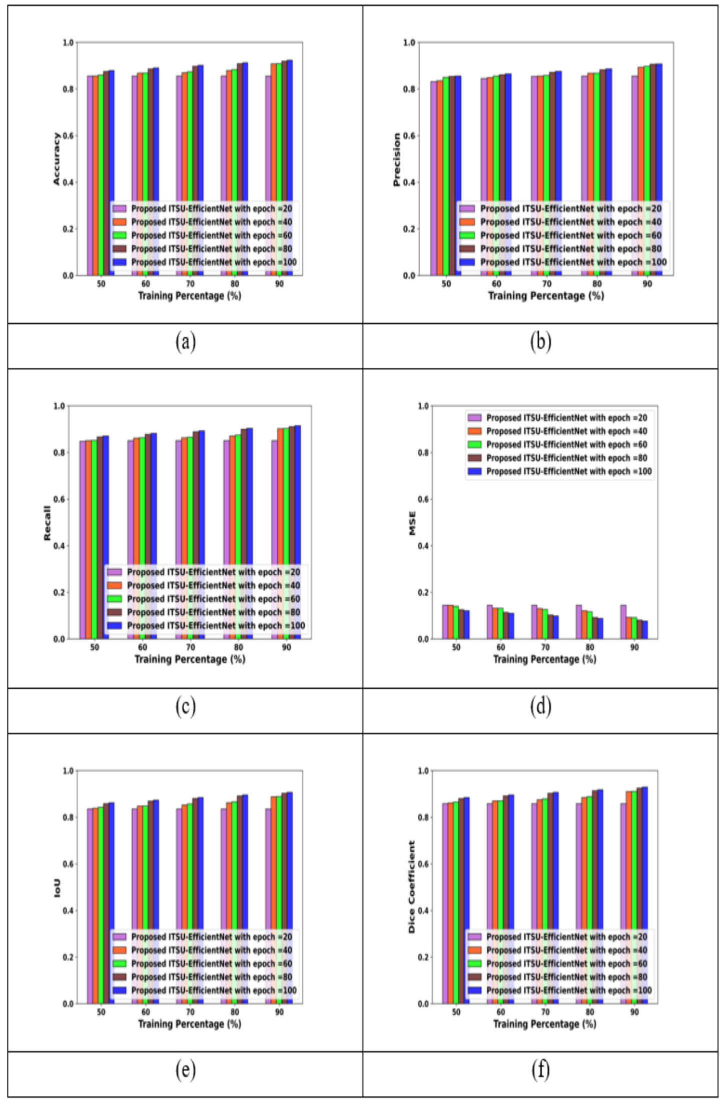

Fig. 6. Performance assessment based on (a) Accuracy, (b) Precision, (c) Recall, (d) MSE, (e) IoU and (f) Dice coefficient.

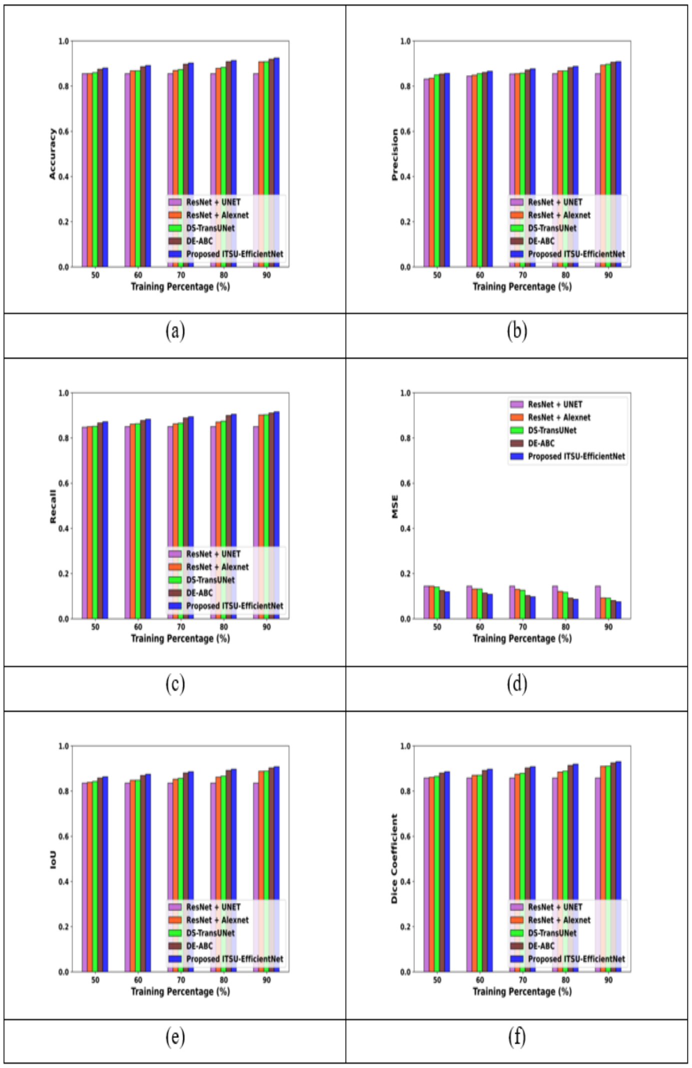

Fig. 7. Comparative assessment of proposed method with conventional methods based on (a) Accuracy, (b) Precision, (c) Recall, (d) MSE, (e) IoU and (f) Dice coefficient.

E. Comparative Discussion

The comparative discussion of the proposed method with existing UNet based methods of skin cancer segmentation approaches is depicted in Table II.

The analysis depicts the superior performance of the ITSU-EfficientNet based on the various assessment measures like Dice coefficient, Precision, Recall and IoU. The reason behind the superiority of the model is the hybrid deep learning model along with the optimal network parameter learning capability. The EfficientNet offers the enhanced performance in skin lesion segmentation with minimal number of parameters. Also, the UNet provides the superior performance in the image segmentation task. Thus, the hybridized model offers the superior performance in skin lesion segmentation compared to the comparative model. Besides, the optimal network parameters tuning using the ITSO algorithm minimizes the information loss during the training phase through the global best solution. The deep learning model with minimal loss elevates its generalization capability and hence it provides the superior performance while analyzing the performance with unknown test image.

TABLE I. COMPARATIVE ASSESSMENT BY VARYING THE TRAINING DATA

Methods/ Training Percentage	50	60	70	80	90
Accuracy					
ResNet+ UNet	0.81	0.85	0.86	0.86	0.87
ResNet + AlexNet	0.82	0.86	0.87	0.87	0.87
DS-TransUNet	0.88	0.88	0.88	0.88	0.88
DE-ABC	0.88	0.89	0.90	0.91	0.93
ITSU-EfficientNet	0.90	0.91	0.92	0.92	0.94
MSE					
ResNet+ UNet	0.19	0.15	0.14	0.14	0.13
ResNet + AlexNet	0.18	0.14	0.13	0.13	0.13
DS-TransUNet	0.12	0.12	0.12	0.12	0.12
DE-ABC	0.12	0.11	0.10	0.09	0.07
ITSU-EfficientNet	0.10	0.09	0.08	0.08	0.06
Precision					
ResNet+ UNet	0.80	0.83	0.84	0.84	0.85
ResNet + AlexNet	0.80	0.84	0.85	0.85	0.86
DS-TransUNet	0.86	0.87	0.88	0.88	0.88
DE-ABC	0.87	0.88	0.88	0.91	0.92
ITSU-EfficientNet	0.90	0.90	0.90	0.92	0.94
Recall					
ResNet+ UNet	0.79	0.82	0.83	0.83	0.84
ResNet + AlexNet	0.79	0.83	0.84	0.84	0.84
DS-TransUNet	0.85	0.86	0.87	0.88	0.88
DE-ABC	0.86	0.87	0.88	0.91	0.93
ITSU-EfficientNet	0.90	0.90	0.90	0.92	0.94
IoU					
ResNet+ UNet	0.78	0.82	0.83	0.83	0.83
ResNet + AlexNet	0.78	0.82	0.83	0.83	0.84
DS-TransUNet	0.85	0.85	0.86	0.86	0.86
DE-ABC	0.85	0.86	0.86	0.89	0.91
ITSU-EfficientNet	0.88	0.88	0.88	0.90	0.92
Dice Coefficient					
ResNet+ UNet	0.80	0.84	0.85	0.85	0.86
ResNet + AlexNet	0.81	0.84	0.85	0.85	0.86
DS-TransUNet	0.87	0.87	0.88	0.89	0.89
DE-ABC	0.88	0.88	0.89	0.91	0.93
ITSU-EfficientNet	0.90	0.90	0.90	0.92	0.94

TABLE II. COMPARATIVE DISCUSSION

Method	Dice Coefficient	Precision	Recall	IoU
Unet with Focal Tversky Loss[39]	85.6	89.6	92.6	-
MultiScale Residual Fusion N [40]	88.24	93.48	88.93	83.73
Dense Residual Unet [41]	86.1	91.1	88.2	-
Double Unet[42]	89.62	94.59	87.8	82.12
∇^N -Net [43]	89.6	97.07	96.36	88.83
ITSU- EfficientNet (Proposed)	94.36	91.33	99.17	92.9

Also, the additional artefact removal process removes the noise from the image and enhances the quality of the image. Hence, the combined performance of the proposed skin lesion segmentation process accomplished the superior performance.

V. CONCLUSION

This research introduced an optimized deep learning model named ITSU-EfficientNet for the skin lesion segmentation approach. The newly devised TSU-EfficientNet combines the ITSO algorithm, UNet and EfficientNet, wherein the learnable parameters of the deep learning model are tuned using the ITSO algorithm. Here, the balanced intensification and diversification phase of the ITSO algorithm eliminates information loss during the data learning phase. Also, the hybrid deep learning model with the combined UNet and EfficientNet provides the enhanced accuracy in skin lesion segmentation. The faster convergence rate of the algorithm reduces the computation time without compromising the performance of the model. The performance assessment based on various measures like Accuracy, MSE, Precision, Recall, IoU, and Dice Coefficient and acquired the values of 0.94, 0.06, 0.94, 0.94, 0.92 and 0.94 respectively. However, the proposed model is not used to analyze the skin lesion classification using the segmentation outcome. Hence, in the future a novel classification method will be devised for identifying the skin lesion type and its severity.

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