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A Brief Survey of State-of-the Art Deep Learning Algorithms for Region of Interest Segmentation in Dermoscopic Images

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ABSTRACT

Improving the quantitative analysis of automatic skin cancer detection at early stages relies heavily on skin lesion-region segmentation from dermatology images. However, because of the vast variation of melanoma and uncertain boundaries of the lesion, the automatic segmentation of extract lesion is quite difficult. Visual inspection of skin lesion images for the purpose of diagnosing skin cancer has proven to be a laborious process. It is a painstaking and time-consuming to manually examine skin lesions for the presence of melanoma. Medical imaging evaluation and in particular skin lesion image evaluation, has benefited from the proliferation of deep learning models and other machine learning approaches made possible by the exponential growth in computational capability in recent few years. Although these models have shown remarkable results, there are still obstacles to overcome when using these methods to analyze skin lesion images because of the special and intricate nature of these images. This study provides an exhaustive review of methods for segmentation of skin lesion from dermoscopic images for cancer analysis, in order to help researchers create effective models that can detect melanoma from skin lesion images automatically and effectively. This work aims to offer an up-to-date survey related to the region of interest (ROI) segmentation. In this paper firstly we discuss the existing work related to the lesion ROI detection, and then move towards the dermoscopic image analysis techniques like pre-processing, ROI segmentation and their applications. We have also performed a comparative analysis of results based on the parameters for evaluation, that helps to identify the best approach for diagnosis and their limitations. We conclude by investigating and evaluating the efficacy of the cutting-edge approaches used in the well-attended ISBI, PH2, ISIC 2018 and 2019 skin lesion image analysis contests and challenges.

KEYWORDS: Image Processing, Dermoscopic Images of Skin Lesion, Lesion Region of Interest, Pre-processing, Traditional and Improved Segmentation, Deep Learning.

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INTRODUCTION

Analysis and evaluation of medical images for the diagnosis of melanoma relies on region of interest (ROI) segmentation to identify areas of interest for diagnosis or further processing. Most of the traditional ROI segmentation from medical images uses image processing and their combination with meta heuristic approaches. To define anatomical structures and anomalies, thresholding, edge detection, and morphological operations are used by the various researchers. Thresholding can identify bones or soft tissues in X-ray or MRI images based on pixel intensity. Erosion and dilation refine segmented regions, while edge detection techniques discover boundaries. Traditional methods may struggle with image quality, noise, and anatomical complexity despite their popularity. They may also need human parameter adjustment, making them less adaptable to varied datasets. To improve ROI segmentation accuracy and resilience, medical imaging is progressively integrating older methods with more advanced algorithms like machine learning. According to report submitted by ***Masood and Al-Jumaily*** in 2013 [1] and ***Adeyinka and Viriri*** in 2018 [2], who worked on a computer vision task for the recent development of the application of machine learning techniques, which have substantially enhanced diagnosis and early detection of incurable malignant skin diseases. From the perspective of dermoscopic image analysis, manual screening based on visual inspection have long been employed to diagnose and identify skin cancer disorders. But, according to a report submitted by ***Yu et al.*** in 2016, the visual evaluation of skin lesion by dermatologists is laborious, time-consuming, arbitrary, and prone to error [3]. This is primarily due to the complex characteristics of skin lesion imaging, which necessitates unambiguous recognition of skin lesion pixels for the purposes of analysis, interpretation, and understanding dermoscopic images of skin lesions [4–7]. Segmentation of exact lesion may be challenging due to various factors, including the presence of hair on region, blood vessels, lubricants and other forms of disturbance in the images [8]. Additionally, the lack of contrast between the region in focus and the surrounding epidermis complicates accurate segmentation from the dermoscopic image. In conclusion, the diverse array of sizes for skin images, their contours, and colors may impede the ability of the manual methods to attain higher degrees of precision. As a consequence, manual screening has become arduous for dermatologists, compelling them to employ automatic computerized diagnostic tools to analyse skin lesions and aid in prompt decision-making [9]. A collection of low-level pixel processing algorithms is frequently employed in conventional medical image diagnostics systems by numerous researchers. The pipeline process for segmenting, detecting and diagnosing skin cancer has been succinctly outlined in Fig. 1 that consists of the following primary processing approaches: pre-processing, ROI segmentation, feature mining from ROI, and classification of the region from skin lesions [10-11].

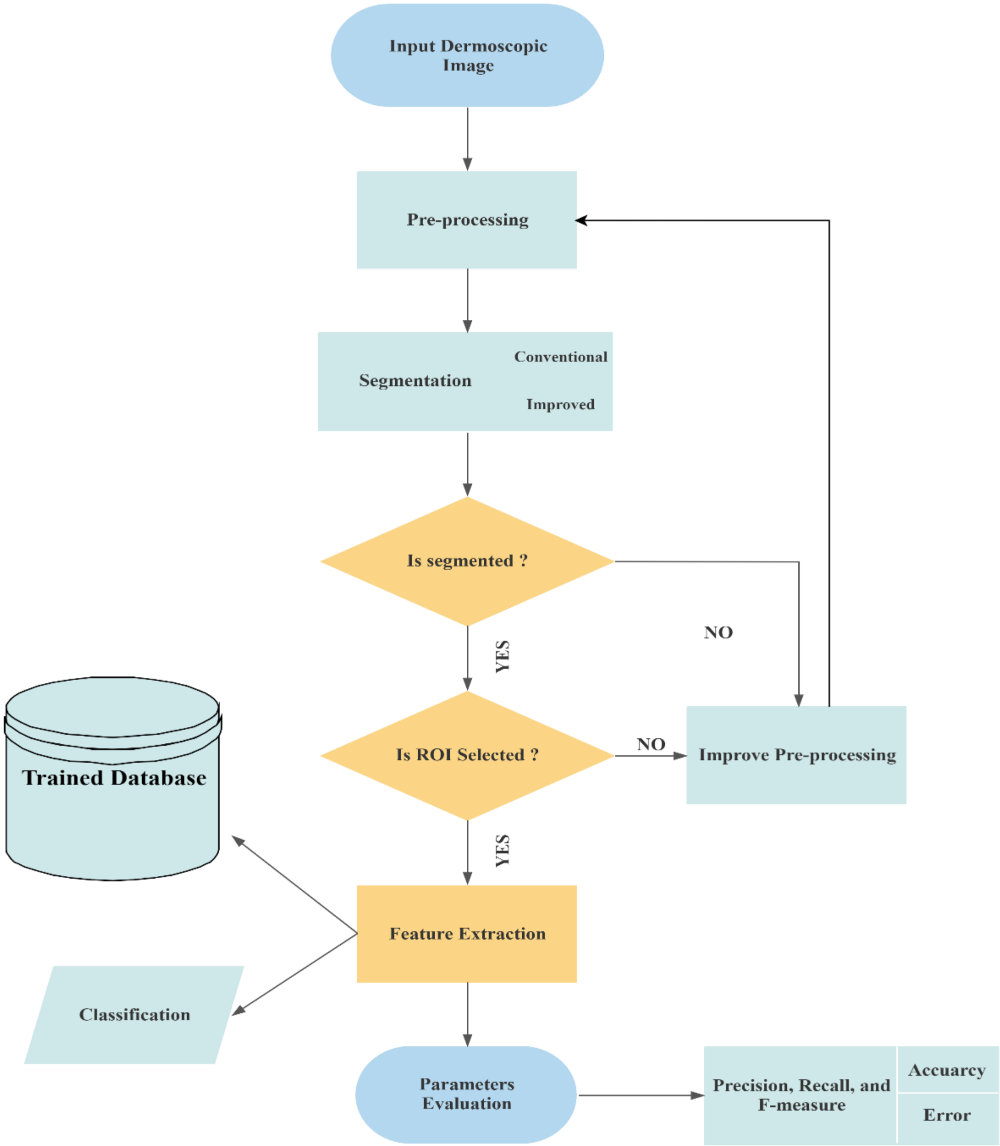

Fig. 1: System Pipeline for Detection and Analysis of Skin Cancer

In order to achieve dependable and efficient segmentation of skin lesions from dermoscopic images, various approaches based on artificial intelligence have been employed, including but not limited to Particle Swarm Optimization (PSO), Fuzzy Logic (FL), Artificial Neural Networks (ANN), Genetic Algorithm (GA), and more deep learning or machine learning methodologies [12]. The lesion features are extracted using multiple extraction techniques in order to train and recognize the skin cancer from the dermoscopic images [13]. Finally, the collected set of features are fed into training and classification algorithms to determine the type of skin cancer present on the skin dermoscopic images. ANN, Support Vector Machine (SVM), Decision Tree (DT), and FL are among the most commonly used classification and training algorithms for cutaneous lesion data [14]. Deep learning approaches have recently attained state-of-the-art performance in skin lesion analysis to the point that dermoscopic images may now be used to diagnosis skin illnesses [15], but there are still lots of drawbacks and challenging factors that are unsolved. The following is a list of the contributions that the review work has made:

- ❖ Firstly, we discussed the existing work related to the lesion ROI detection to identify the gaps based on recent published work.
- ❖ We focused on the dermoscopic image analysis techniques like pre-processing, ROI segmentation and their applications.
- ❖ To identify the efficiency of existing models and find out the most improved models for ROI segmentation based on the performance analysis.

The structure of this review article is organized as follows. We focus on the lesion ROI detection and their challenges in details in the Section II, then dermoscopic image analysis techniques with their advantages and disadvantages that are mentioned in the Section III. A parametric performance evaluation of cutting-edge algorithms and methodologies for segmenting skin lesions is presented in Section IV and, finally we discuss the conclusion in Section V with future possibilities.

LESION REGION OF INTEREST DETECTION CHALLENGES

Due to variation in quality of dermoscopic images and their source, which might contributory to the difficulty in recognizing skin lesions [16]. Due to the wide variation in the appearance of skin colour, skin lesion detection and their identification is a difficult as well as time-consuming process [17]. A variety of images illustrating some of these obstacles is presented in Fig. 2 for skin lesions.

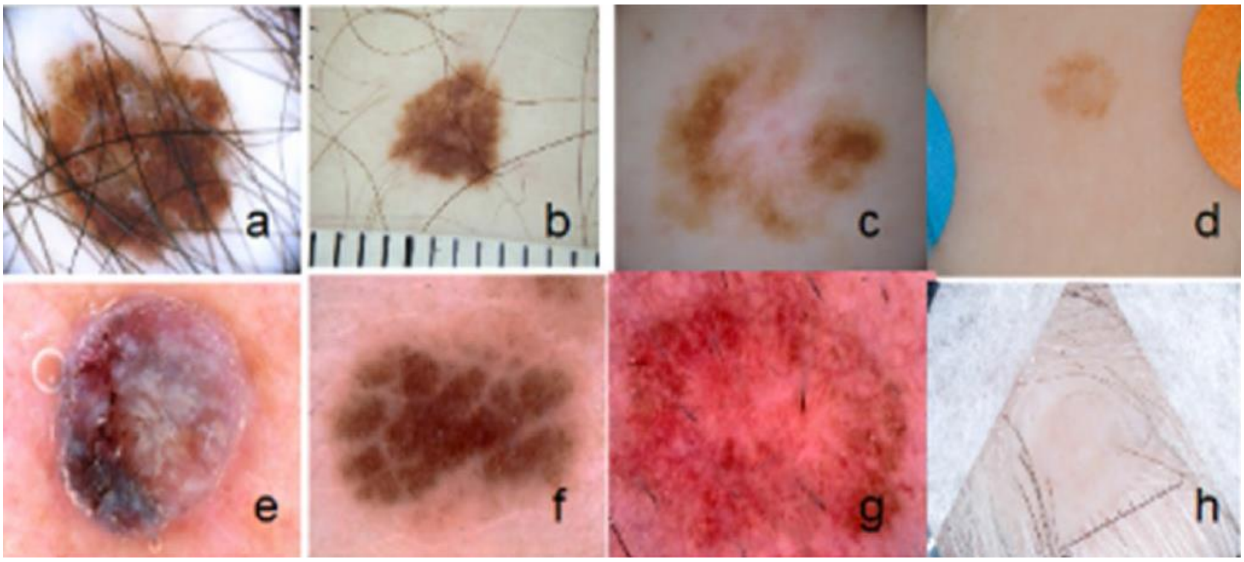

Fig. 2: Challenging factors: (a) hair on lesion, (b) ruler mark with lesion, (c) poor quality, (d) chromatic radiance, (e) mark of bubbles, (f) asymmetrical skin perimeters, (g) vascular network, and (h) image frame

The complexity and variety of skin disorders provides a number of obstacles when it comes to the detection of lesions in dermoscopic pictures of the skin. When it comes to addressing these issues in the ROI detection, a mix of advanced image processing techniques, machine learning algorithms, and the incorporation of domain-specific knowledge is required. Among the most significant difficulties are the following:

Shape-Size Variation: The extensive range of skin lesions that are known lead to the difficulty in precise diagnosis which is exceedingly challenging for researchers. The location, size, and form of lesions vary greatly, and for accurate analysis of cancer from images, image pre-processing methods are necessary.

Occurrence of Noise and Artifacts: Artifacts and noise introduced during the acquisition of skin lesion dermoscopic images are commonly known as a type noise. The existence of such artifacts makes it challenging to discern the specific type of cancer present in the images. Compromising signals which were not present in the initial dermoscopic image have the potential to disrupt image interpretation when applied manually or through computer-assisted skin lesion segmentation methods.

Asymmetrical Boundaries: Hazy and irregular borders in some skin lesion images hamper contour refining and boundary localization protocols. Dermoscopic images may not provide precise skin lesion borders during pre-processing for simple asymmetry prediction.

Poor Quality: Contrast and brightness from nearby tissues can also be reason of difficulty in the recognition of cancer. The poor contrast between cancerous and normal surrounding skin makes precise segmentation of the lesion difficult and should be overcome.

Color Radiance: The color texture, as well as light rays and reflections, might impact the lighting of the dermoscopic skin lesion images, resulting in multiresolution.

DERMOSCOPIC IMAGE ANALYSIS TECHNIQUES

3.1 Pre-processing Techniques

Pre-processing of a dermoscopic image is mostly used to get image ready for faster processing with maximum accuracy during their recognition. According to ***Zaqout*** in 2019, the concept of pre-processing includes lots of steps such as converting an image to grayscale, quality enhancement, noise filtering, and generating a binary picture [18]. The conversion of a lesion image to grayscale involves transforming the colors (3D) to shades of grey (2D). Quality enhancement methods, on the other hand, include contrast adjustment (which expands the histogram of an image to improve visibility), intensity adjustment (which enhances the intensity values of an image to produce a high-quality display), and histogram equalization (which evenly distributes pixel intensities across the entire range to increase the overall contrast of images). Noise detection and their removal is a technique used to exclude undesired pixel sets from a picture that is produced through image capturing and binarization. This process involves converting the image into a grayscale representation and reducing the information inside it to simply black (0) and white (1) values. In the pre-processing step, morphological procedures such as erosion and dilation are sometimes carried out to extract features and determine the placement of objects in a dermoscopic image. When it comes to improving the quality of skin lesion images and getting them ready for further analysis or diagnosis, such as lesion detection or classification, preprocessing is an extremely important step. Several preprocessing techniques are typically utilized for images of skin lesions, including the following:

The normalization of lesion colors: It is possible to reduce the effect that differences in ambient lighting can have on dermoscopic images by standardizing the color properties of individual images. In order to guarantee that all images have consistent color representations, techniques such as color normalization are utilized.

Controlling the Noise in Image: There is a possibility that dermoscopic images contain noise, which could potentially compromise the accuracy for later analysis. For the purpose of minimizing noise while maintaining the integrity of essential features, filters such as median filters and Gaussian filters are utilized.

Scaling of the Dermoscopic Image: The process of resizing photographs to a standard resolution helps to ensure that all datasets are consistent with one another. Additionally, it lessens the intricate nature of the computations involved in the post processing steps.

The enhancement of lesion region contrast: It is possible to boost the visibility of lesions by adjusting the contrast of the relevant dermoscopic images. The overall image quality can be improved by the use of techniques such as histogram equalization (may be limited adaptive) or contrast stretching techniques.

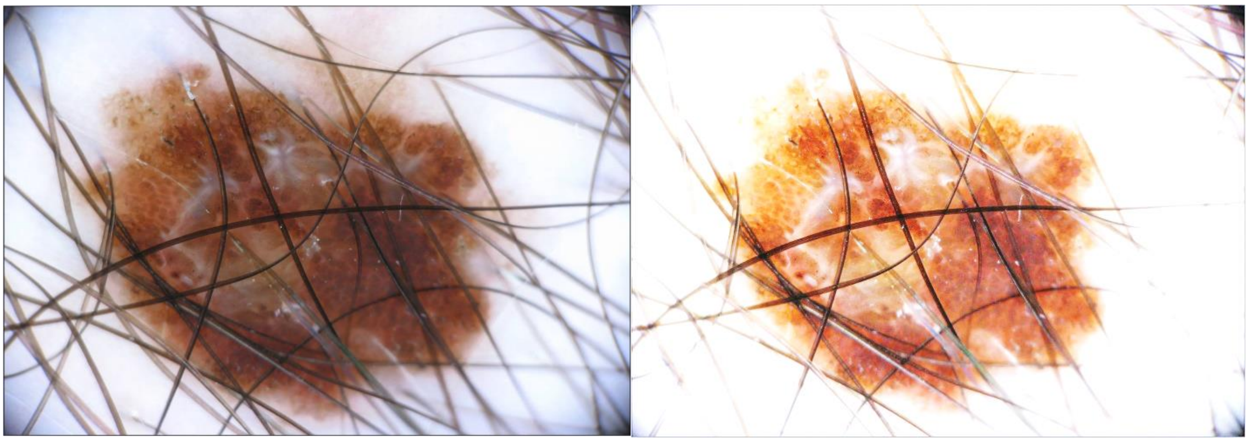

Fig. 3: Enhancement of Lesion Region Contrast

Hair Removal from the lesion region: One of the most important pre-processing steps in skin imaging is the removal of hair from the lesion location. This is especially important in dermoscopic images, where hair can conceal the lesion and make it more difficult to do an appropriate analysis. A variety of concepts are used by the researchers to remove the hair form lesion location and to clean the skin lesion image that help to reduce the irrelevant features.

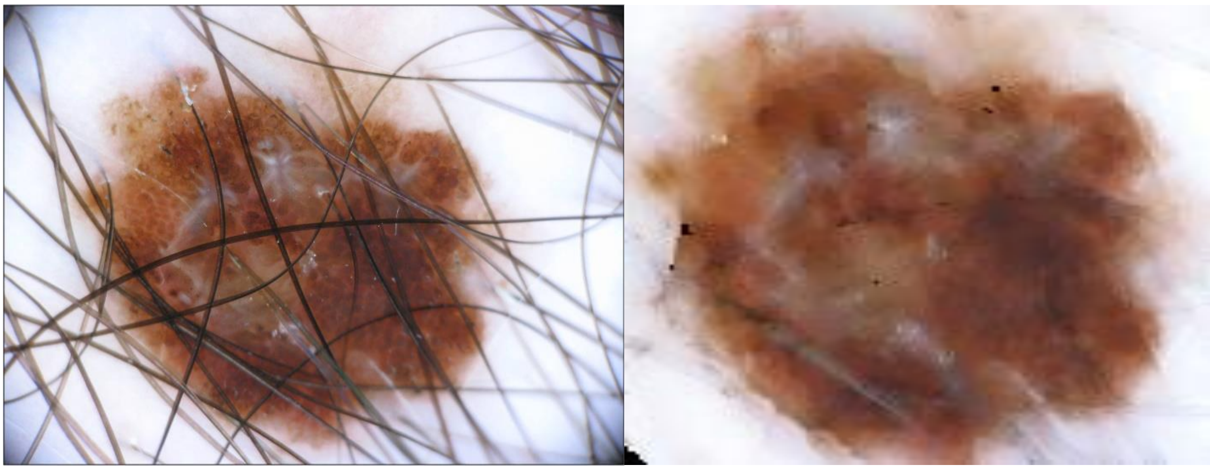

Fig. 4: Hair Removal from Lesion Region

Extraction of ROI: It is essential to locate and isolate the area that has the lesion after it has been identified. Isolating the relevant

area for subsequent analysis can be accomplished with the assistance of techniques such as segmentation or manual annotation.
Standardization and Normalization of Image: During the process of machine learning tasks, normalizing pixel values to a standard scale (for example, 0 to 1) and standardizing features can be helpful in training models and improving convergence.

Flipping and Rotating: The capacity of the model to generalize can be improved by increasing the variability of the training set through the application of random rotations or horizontal flips, which can be considered an augmentation of the dataset.

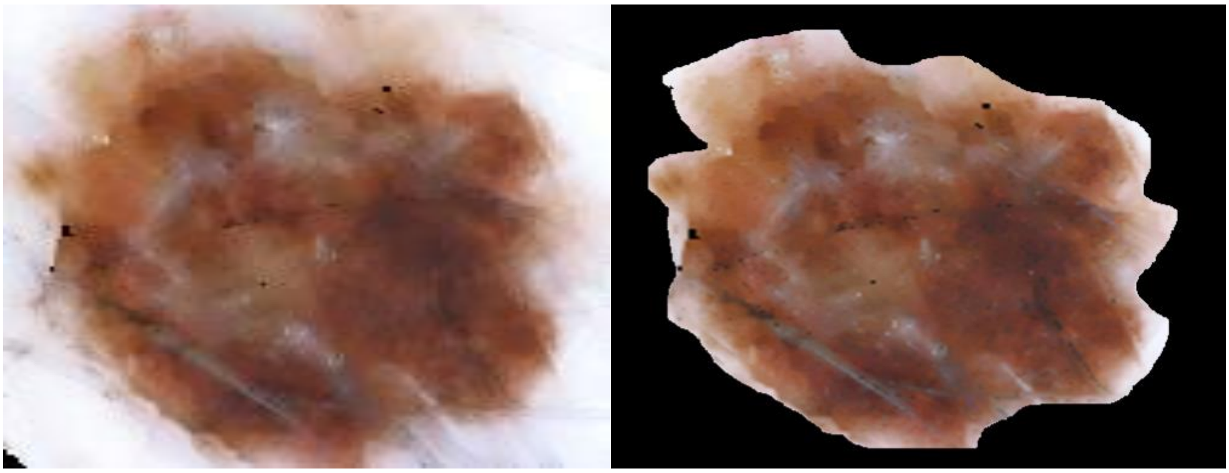

Fig. 5: ROI Extraction from Dermoscopic Images

Color Space Transformation: The process of converting images to other color spaces, such as RGB to Grey, RGB to HSV etc., can occasionally improve particular features or make certain components of the image more distinguishable.

Detection of the Edge: In order to better define the limits of the lesion and hair line, it is helpful to highlight the margins within the image. In order to accomplish this goal, edge detection methods, such as the canny edge detector, can be utilized or implemented.

Note that the method chosen relies on the photos and analysis needs. Hair removal while maintaining lesion features may require multiple steps. To ensure accuracy and generalizability, these strategies must be tested on a broad dataset.

3.2 Segmentation Techniques

Automating diagnosis of a skin lesion image relies heavily on image segmentation and it's a crucial step in detection and classification process of melanoma. Basically segmentation process helps to separate the relevant and irrelevant portion of an image, and selects the most useful Region of Interest (ROI) [19]. There are lots of approaches that are available for handcrafted features-based segmentation such as threshold-based, edge and region-based, and intelligence-based supervised segmentation. ANN, machine as well as deep learning algorithms are examples of intelligent-based segmentation approach and Table 1 compares and contrasts different segmentation approaches, highlighting their advantages and disadvantages.

Table 1: A comparison of conventional and modern skin lesion segmentation methods

Techniques	Description
Threshold and clustering based [20-23]	A strategy to partition images in which the foreground (lesion region) and background (extra) are separated from one another based on a threshold value or number of clusters. This method begins with the selection of an initial threshold value, and then proceeds to divide the initial image into sections. **Advantages:** 1. Implementation is quick and easy. Knowledge of image spatial characteristics is not needed. 2. Thresholding and clustering are computationally efficient and easy to use. Real-time or resource-constrained applications benefit from their simple computations and operations. **Disadvantages:** Noise and intensity inhomogeneity affect it.
Edge and Region based [24-26]	These methods use search-based procedures to find regions of interest in dermoscopic images, including edge detection and region identification. **Advantages:** The approaches meet homogeneity criteria and use split and combine hybrid strategy for enhanced segmentation. **Disadvantages:** The main drawbacks are manual seed point initialization for specific regions processing and noise sensitivity.
Conventional intelligence-based [27-31]	These artificial intelligence-based systems analyze images using learning, reasoning, and perception from enormous datasets. Supervised and unsupervised skin lesion segmentation methods exist and both are appropriate to segment the ROI. Intelligent segmentation methods like ANN, GA, and Fuzzy C-Means are most popular. **Advantages:** 1. The detection accuracy is consistently higher and has fewer false positives than threshold and region-based segmentation methods.

	2. Models might overfit when the dataset is not representative of the population. **Disadvantages:** It ignores spatial modeling. It is noise-sensitive and has data processing uncertainties.
Deep Learning-based [32]	Deep learning allows multi-layer computer models to learn and represent data at different abstraction levels. Deep learning uses neural networks, hierarchical probability models, unsupervised and supervised feature learning methods. **Advantages:** 1. It represents features from pixels to high-level semantics hierarchically. It subtly captures complex large-scale skin data better than intelligence-based approaches. 2. Deep learning models eliminate human feature engineering by segmenting end-to-end. The model learning low-level and high-level properties from input data improves adaptation to varied lesion presentations. 3. Deep learning models interpret images semantically. This lets them distinguish lesion and non-lesion regions based on visual context and relationships, improving segmentation outcomes. **Disadvantages:** Training is more costly than other methods. Processing a tiny training set consumes time and memory.

Currently, deep learning algorithms have achieved remarkable results in segmenting the regions of lesions, which is a challenging task in computer vision according to ***Al-Masni et al.*** They state that researchers have presented several deep learning models in recent years, which have proven to be successful for segmenting skin lesions [33]. This study critically reviews Deep Convolutional Neural Networks (DCNNs), U-Net, Fully Convolutional Networks (FCNs), and Fully Convolutional Residual Networks (FCRNs) architectures. Below we discuss these approaches:

DCNNs for Lesion ROI Segmentation: It is very effective and commonly employed structures for a range of computer vision tasks, including the segmentation of Region of Interest (ROI) from the dermoscopic images for medical diagnosis purposes. DCNNs utilize convolutional layers to autonomously acquire hierarchical features from input images and then use non-linear activation functions, such as Rectified Linear Unit (ReLU). The ReLU function introduces non-linearity, enabling the neural networks to acquire and comprehend intricate correlations present in the data. To recover spatial resolution and generate the final lesion segmentation map, up sampling layers are employed in the decoder part of the DCNN. For the segmentation of skin lesion from dermoscopic images, in 2017 ***Y Yuan et al.*** carried out study utilizing the concept of DL algorithm named as Deep Fully CNN (DFCNN). In this model, authors used the model to separate skin lesions from the entire dermoscopic image, and a unique loss function based on Jaccard distance was developed by the scientists to re-weight utilizing cross entropy. The trial findings showed that the segmentation approach beat other cutting-edge algorithms yet required less pre- and post-processing procedures for greater accuracy [34].

U-Net Architecture for Lesion ROI Segmentation: The U-Net architecture is a widely used and efficient neural network design for image segmentation tasks, specifically for segmenting ROI from the dermoscopic images. The defining feature of U-Net is its structure, consisting of a contracting pathway followed by an expansive pathway. This design enables the network to efficiently capture both contextual and geographical information. Binary cross-entropy is a frequently employed loss function for binary segmentation applications, such as lesion ROI segmentation. The dissimilarity between the anticipated segmentation map and the ground truth is quantified by this measurement. The architecture that you see in Fig. 6 was designed using the concept of FCN and the operation is akin to an encoder-decoder network, where both the encoder and decoder components consist of convolutional layers. The encoder is equipped with pooling and convolutional layers, while the decoder is equipped with up sampling layers. The model incorporates shortcut skip connections that allow for direct flow of information between the encoder and decoder, bypassing the intermediate layers. Some researchers segment skin lesions using this architecture that helps to pass prior information throughout entire network. Here, segmenting skin lesion images are used by the architecture to estimate pixel probability. Same architecture was proposed by the ***Vesal et al.*** in 2018 that is known as modified SkinNet by applying dilated convolutions to the encoder branch's lowest layer of U-Net architecture [35]. The U-Net shortcut skip connection loses image information and the decoder portion recovers feature maps poorly. The upgraded UNet architecture is shown in Fig. 6.

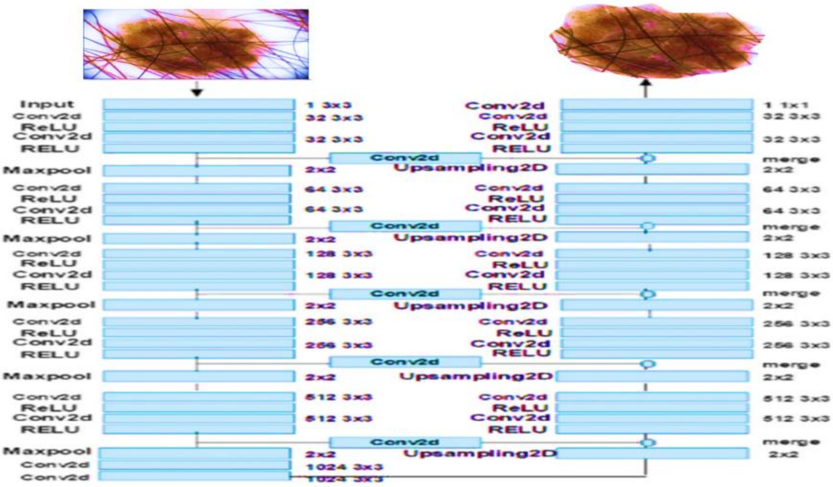

Fig. 6: Architecture of SkinNet [35]

FCN for Lesion ROI Segmentation: In 2017, ***Bi et al.*** developed a multi-stage FCN that leverages the parallel integration (PI) strategy to effectively distinguish skin lesions. This design incorporates convolutional layers as well as pooling layers. The PI methodology was implemented to enhance the demarcation of the segmented skin lesions. The system exhibited outstanding performance, with a segmentation accuracy of 95.51% and a dice coefficient score of 91.18% when assessed on the ISBI 2016 dataset [36].

FCRNs for Lesion ROI Segmentation: The combination of FCNs with residual learning is employed in FCRN for the purpose of aROI segmentation. FCNs are specifically built for performing pixel-wise segmentation tasks from start to finish, and the use of residual learning techniques enhances the training of deeper networks with more efficiency. To preserve spatial information and allow pixel-wise predictions, FCRNs adhere to a completely convolutional architecture. This means that convolutional layers are utilized throughout the network. Lesion ROI segmentation is one of the many segmentation jobs that benefit from this architecture. The introduction of residual blocks allows for residual learning. The activation functions of each convolutional layer in a typical residual block are Batch Normalization and ReLU. The network is able to learn residual mappings through the skip connection, which facilitates the training of deeper networks.

After description of such deep learning algorithms for lesion region segmentation, we present a performance analysis of existing work on standard datasets in the next section of articles.

EXISTING WORK PERFORMANCE ANALYSIS

Benchmark datasets and conventional skin lesion dermoscopic image libraries are essential for evaluating skin lesion analysis models. These datasets contain standardized images with annotations for lesion segmentation, classification, and detection and are widely used in research. Here are some popular skin lesion image datasets or libraries for model evaluation:

DERMOFIT: It is a dataset specifically created to assess the performance of skin lesion segmentation algorithms. The dataset comprises images with different resolutions and skin states, which makes it appropriate for evaluating the resilience and generalization abilities of segmentation models. This is owned by the University of Edinburgh and it contains total 1300 dermoscopic images of 331 Melanocytic Nevus, 257 Seborrhoeic Keratosis, 239 Basal Cell Carcinoma (BCC), 96 Haemangioma, 88 Squamous Cell Carcinoma (SCC), 78 Intraepithelial Carcinoma, 76 Melanoma, 65 Dermatofbroma, 45 Actinic Keratosis and 24 Pyogenic Granuloma images.

PH2: The primary focus of the PH2 dataset is on dermoscopic images specifically related to melanocytic lesions and it contains total 200 dermoscopic images of melanocytic lesions with a resolution of 768×560. There is a total of three melanocytic lesions which includes: 80:80:40 for common, atypical and melanomas separately.

HAM10000: The dataset is referred to as Human Against Machine and it involves total10,000 training skin images includes a diverse set of images covering various skin lesions. It is annotated for lesion classification and has been used in challenges such as the ISIC Skin Lesion Classification Challenge. The dataset comprises 10015 dermoscopic images that is mostly utilized for academic machine learning endeavors.

UDA-1: It is also known as the University of Florence Dermatology and Skin Cancer dataset, offers dermoscopic images of exceptional quality together with corresponding annotations. It contains images of several lesion kinds, making it a helpful resource for skin lesion analysis study.

PHC-U373: The PHC-U373 dataset comprises dermoscopic images that are utilized within the PH2 dataset. It is commonly employed for benchmarking and comparing the efficiency of segmentation and classification algorithms.

BCN20000: The BCN20000 dataset is an extensive collection of skin lesion images. The label is intended for classification tasks, making it appropriate for assessing the ability of models to differentiate between various types of lesions.

International Symposium on Biomedical Imaging (ISBI) 2017: The collection comprises approximately 10000 dermoscopic skin lesion images, intended for medical diagnosis and scientific research purposes. A portion of the dermoscopic images of skin lesions has been annotated and marked by acknowledged experts in the field of skin cancer.

International Skin Imaging Collaboration (ISIC) 2018: The ISIC archive is an extensive dataset comprising a vast assortment of skin lesion images which helps researchers. The collection has images depicting many skin disorders, including melanoma, nevus, and basal cell carcinoma. This dataset comprises a total of 2594 skin images, additionally it includes 1000 test images sourced from HAM10000 by ***Codella et al.*** in 2018 [37].

ISIC 2019: The collection includes 25331 JPEG training data skin images with metadata like age, sex, and general anatomic site. It also includes a corresponding label indicating standard lesion diagnoses. Additionally, it includes a collection of 8238 JPEG photos depicting skin lesion test data. Some sample of ISIC 2019 dataset are shown in Fig. 7.

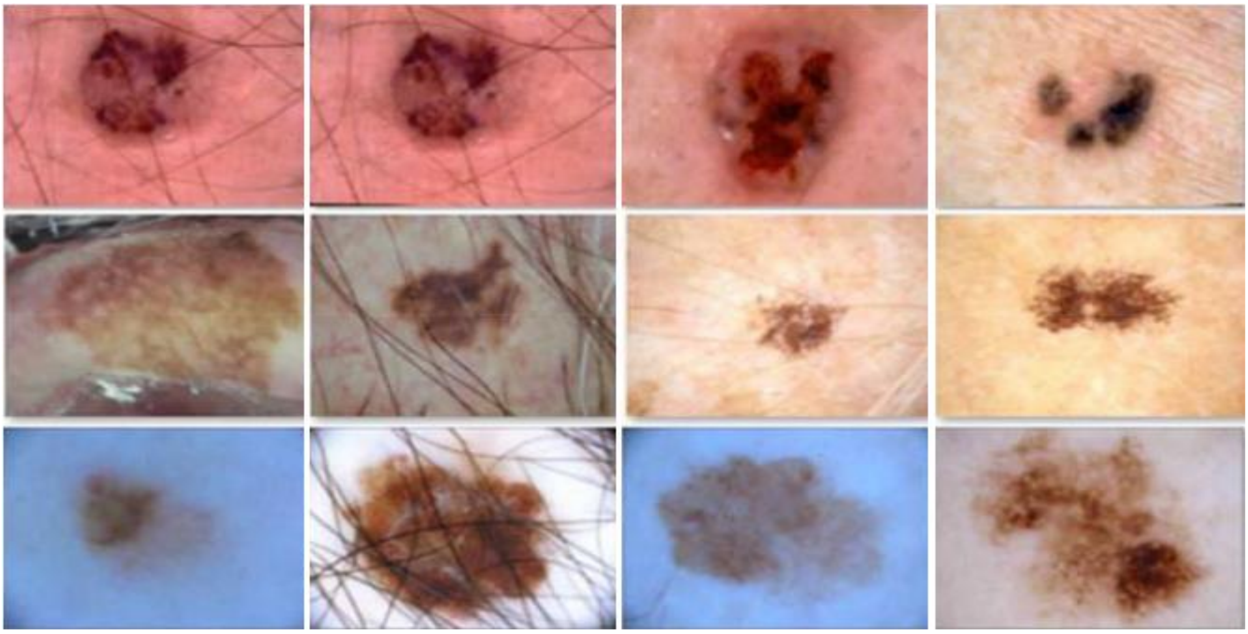

Fig. 7: ISIC 2019 Dataset Sample

Based on the above-mentioned dataset of dermoscopic images, most of the researcher are performed their evaluation to validate the models and the performance analysis of state-of-the-arts simulation are described below. Table 2 shows the findings of a few of the most productive state-of-the-art approaches employed at ISIC 2018-19, ISBI and PH2 datasets.

Table 2: Evaluation results of advanced algorithms for skin lesion segmentation

Techniques	**Evaluation Parameters in %**					
	Reference	**Accuracy**	**Recall**	**Specificity**	**Dice Coefficient**	**Jaccard Coefficient**
AlexNet	[38]	94.0	90.1	95.1	87.6	83.7
Encoder & Decoder Network	[39]	94.2	90.6	96.3	89.8	83.8
Ensemble-VGG16, Dense-Net, U-net and Inception-V3	[40]	94.5	93.4	95.2	90.9	83.7
Encoder & Decoder + ResNet34 and DeCov-Networks	[41]	94.3	91.8	96.4	90.0	83.4
FC Encoder & Decoder Network with CRF	[42]	94.5	94.0	94.2	90.3	83.7
U-Net with DeepLabV3	[43]	94.7	94.5	94.5	90.3	83.6
FCN + Region-Proposal Network (RPN) and CRF	[44]	93.7	92.1	91.8	89.8	83.6
Mask-RCNN	[45]	93.9	90.4	96.8	89.0	82.3
Mask R-CNN model with ResNet50	[46]	93.7	93.6	94.3	89.0	82.2
U-Net Variants	[47]	93.8	94.5	93.9	89.0	81.6
U-Net	[48]	93.7	87.9	97.9	89.0	82.6
FCN-8 s and U-Net	[49]	90.2	–	–	–	78.3
DCNN-9 Architecture	[50]	95.6	96.3	96.5	–	–
Fine-Tuned CNN Model	[51]	96.7	96.4	95.9	–	91.7

From Table 2, results of the best models for ISIC 2019, PH2 and ISBI is fine-tuned CNN model which is proposed by ***A. Bibi et al.*** in 2022 [51]. Tables 2 shows the segmentation results of skin lesion region extraction from the dermoscopic images through the improved deep learning models. Lesion ROI extraction through fine-tuning-based CNN for standard dataset includes tailoring a pre-trained CNN model to a particular goal, such lesion segmentation. Create lesion segmentation layers at the conclusion of the stripped CNN architecture. Convolutional layers, up sampling layers, and a final convolutional layer with sigmoid activation function for binary segmentation are usually added. Researchers tune learning rate, batch size, and training epochs with hyperparameters and tried different values for best results. Dermoscopic image lesion ROI segmentation has various real-time applications that can help dermatologists diagnose lesions. Possible real-time applications are listed below:

1. Detecting skin cancer early: Automated lesion segmentation can detect skin cancer early by emphasizing problematic areas in dermoscopic images. Dermatologists can easily recognize malignancy in segmented lesions and prioritize additional studies.
2. Remote consultations and telemedicine: Dermatologists can analyze lesion ROI segmentations in real time via telemedicine. Smartphone apps allow patients to capture dermoscopic images and securely transmit them for remote consultations, enhancing access to professional counsel.
3. Over Time Lesion Tracking: Real-time segmentation tracks lesions over visits. Dermatologists can track lesion size, shape, and color changes by comparing segmented photos over time. This helps track skin cancer patients over time.
4. Automated Lesion Measurement: Calculating lesion dimensions automatically with accurate lesion segmentation provides quantitative data for analysis. Dermatologists can utilize this information to track lesion size changes.
5. System Supporting Decisions: Real-time lesion segmentation in decision support systems aids dermatologists in diagnosis. The segmentation results can be used with other clinical data to diagnose.
6. Dermatology Training Materials: Real-time lesion segmentation can be used in dermatology and medical student teaching. Interactive platforms with annotated dermoscopic images and rapid lesion segmentation feedback improve learning.
7. Automated Lesion Classification: Real-time segmentation and lesion classification algorithms automate lesion categorization by predetermined criteria. This helps dermatologists swiftly detect benign and malignant tumors.
8. Improved Patient Communication: Patients can communicate visually using real-time lesion segmentation. Dermatologists can show patients segmented images of lesions and emphasize the need of monitoring key aspects.
9. Smartphone Self-Examination Apps: Smartphone apps with real-time lesion segmentation enable self-examination. Users can take dermoscopic photos of skin lesions and get instant feedback on segmented areas for proactive skin monitoring.

Lesion ROI segmentation improves dermatological diagnoses, workflows, and patient outcomes in these real-time applications. Dermatology can benefit greatly from artificial intelligence and real-time image processing for accurate skin lesion assessments as technology advances. After survey of lots of existing research work related to skin lesion segmentation from dermoscopic images, we conclude overall summary of this survey in the next section of article.

CONCLUSION

The survey provides a brief comprehensive and evaluative inspection of the most advanced techniques used to analyze dermoscopic images of skin lesions to segment the exact region of lesion. This is a thorough examination of the methods and algorithms employed in analyzing skin lesion images to identify cases of melanoma, nevus, basal cell carcinoma and many more skin lesion diseases that is a kind of skin cancer. These techniques encompass pre-processing procedures, and segmentation algorithms including both traditional as well as deep learning-based methods. We also looked into how well the top algorithms works on the standard dataset like ISIC 2018 and 2019, ISBI and PH2 images datasets of skin lesions. We took a close look at the top algorithms like DCNNs, U-Net, FCNs, CNNs and FCRNs architectures. Overall, it appears that ensemble models containing state-of-the-art models like AlexNet, ResNet, DenseNet121, InceptionV3, and fine-tuning approaches achieve remarkable results. Nevertheless, training these models is laborious and resource intensive. It was found that when deep learning models are applied to properly segmented and pre-processed images, the images perform better in segmentation when measured using evaluation metrics including accuracy, sensitivity, specificity, dice-coefficient, jaccard-coefficient. It is advised to use pre-processing methods like hair removal; lesion region contrast enhancement and deep learning-based segmentation algorithms for better classification performance in future because of their proven effectiveness. Because of their fine-grained appearance, skin lesion images present unique obstacles when analyzed. This will help to overcome the mentioned challenges and fulfill the development of real time application in future.

References:

1. Masood, A., & Ali Al-Jumaily, A. (2013). Computer aided diagnostic support system for skin cancer: a review of techniques and algorithms. International journal of biomedical imaging, 2013.
2. Adeyinka, A. A., & Viriri, S. (2018, December). Skin lesion images segmentation: A survey of the state-of-the-art. In International conference on mining intelligence and knowledge exploration (pp. 321-330). Springer, Cham.
3. Yu L, Chen H, Dou Q, Qin J, Heng P-A (2016) Automated melanoma recognition in dermoscopy images via very deep residual networks. IEEE Trans Med Imaging 36(4):994–1004
4. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118.
5. Adegun, A., & Viriri, S. (2019, September). An enhanced deep learning framework for skin lesions segmentation. In International conference on computational collective intelligence (pp. 414-425). Springer, Cham.
6. Olugbara, O. O., Taiwo, T. B., & Heukelman, D. (2018). Segmentation of melanoma skin lesion using perceptual color difference saliency with morphological analysis. Mathematical Problems in Engineering, 2018.
7. Al-Masni, M. A., Al-Antari, M. A., Choi, M. T., Han, S. M., & Kim, T. S. (2018). Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks. Computer methods and programs in biomedicine, 162, 221-231.
8. Adegun, A., & Viriri, S. (2019, September). An enhanced deep learning framework for skin lesions segmentation. In International conference on computational collective intelligence (pp. 414-425). Springer, Cham.

9. Al-Masni, M. A., Al-Antari, M. A., Choi, M. T., Han, S. M., & Kim, T. S. (2018). Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks. Computer methods and programs in biomedicine, 162, 221-231.
10. Koundal, D., & Sharma, B. (2019). Advanced neutrosophic set-based ultrasound image analysis. In Neutrosophic set in medical image analysis (pp. 51-73). Academic Press.
11. Ünver, H. M., & Ayan, E. (2019). Skin lesion segmentation in dermoscopic images with combination of YOLO and grabcut algorithm. Diagnostics, 9(3), 72.
12. Nasir, M., Attique Khan, M., Sharif, M., Lali, I. U., Saba, T., & Iqbal, T. (2018). An improved strategy for skin lesion detection and classification using uniform segmentation and feature selection based approach. Microscopy research and technique, 81(6), 528-543.
13. Barata, C., Celebi, M. E., & Marques, J. S. (2018). A survey of feature extraction in dermoscopy image analysis of skin cancer. IEEE journal of biomedical and health informatics, 23(3), 1096-1109.
14. Mohan VC, Dharan SA (2019) “A review on skin lesion classification techniques.” International Journal of Engineering Research Technology (IJERT). 8(01)
15. Goceri, E. (2019, November). Analysis of deep networks with residual blocks and different activation functions: classification of skin diseases. In 2019 Ninth international conference on image processing theory, tools and applications (IPTA) (pp. 1-6). IEEE.
16. Aljanabi, M., Özok, Y. E., Rahebi, J., & Abdullah, A. S. (2018). Skin lesion segmentation method for dermoscopy images using artificial bee colony algorithm. Symmetry, 10(8), 347.
17. Naji, S., Jalab, H. A., & Kareem, S. A. (2019). A survey on skin detection in colored images. Artificial Intelligence Review, 52(2), 1041-1087.
18. Zaqout, I. (2019). Diagnosis of skin lesions based on dermoscopic images using image processing techniques. Pattern Recognition-Selected Methods and Applications.
19. Al-Masni, M. A., Al-Antari, M. A., Choi, M. T., Han, S. M., & Kim, T. S. (2018). Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks. Computer methods and programs in biomedicine, 162, 221-231.
20. Emre Celebi M, Wen Q, Hwang S, Iyatomi H, Schaefer G (2013) Lesion border detection in dermoscopy images using ensembles of thresholding methods. Skin Res Technol 19(1): e252–e258
21. Møllersen K, Kirchesch HM, Schopf TG, Godtliebsen F (2010) Unsupervised segmentation for digital dermoscopic images. Skin Res Technol 16(4):401–407
22. Peruch F, Bogo F, Bonazza M, Cappelleri V-M, Peserico E (2013) Simpler, faster, more accurate melanocytic lesion segmentation through meds. IEEE Trans Biomed Eng 61(2):557–565
23. Yüksel ME, Borlu M (2009) Accurate segmentation of dermoscopic images by image thresholding based on type-2 fuzzy logic. IEEE Trans Fuzzy Syst 17(4):976–982
24. Abbas Q, Emre Celebi M, García IF, Rashid M (2011) Lesion border detection in dermoscopy images using dynamic programming. Skin Res Technol 17(1):91–100
25. Emre Celebi M, Kingravi HA, Hitoshi Iyatomi Y, Aslandogan A, Stoecker WV, Moss RH, Malters JM et al (2008) Border detection in dermoscopy images using statistical region merging. Skin Res Technol 14(3):347–353
26. Zhou H, Schaefer G, Celebi ME, Lin F, Liu T (2011) Gradient vector fow with mean shift for skin lesion segmentation. Comput Med Imaging Graph 35(2):121–127
27. Mathew Sh, Sathyakala D (2015) “Segmentation of skin lesions and classifcation by neural network.” Int J Adv Res Electron Commun Eng (IJARECE) Vol 4.
28. Amelio A, Pizzuti C (2013) “Skin lesion image segmentation using a color genetic algorithm.” In: Proceedings of the 15th annual conference ompanion on Genetic and evolutionary computation, pp 1471-1478
29. Xie F, Bovik AC (2013) Automatic segmentation of dermoscopy images using self-generating neural networks seeded by genetic algorithm. Pattern Recogn 46(3):1012–1019
30. Mohamed AAI, Ali MM, Nusrat K, Rahebi J, Sayiner A, Kandemirli F (2017) Melanoma skin cancer segmentation with image region growing based on fuzzy clustering mean. Int J Eng Innov Res 6(2):91–95
31. Zhou H, Schaefer G, Sadka A, Celebi ME (2008) “Anisotropic mean shift based fuzzy c-means segmentation of skin lesions.” In: Proceedings of the 5th international conference on soft computing as trans-disciplinary science and technology, pp 438-443
32. Yuan Q, Tavildar S (2018) An open solution to ISIC 2018 classifcation and segmentation challenges. ISIC
33. Al-Masni MA, Al-antari MA, Choi M-T, Han S-M, Kim T-S (2018) Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks. Comput Methods Programs Biomed 162:221–231
34. Yuan, Y., Chao, M., & Lo, Y. C. (2017). Automatic skin lesion segmentation using deep fully convolutional networks with jaccard distance. IEEE transactions on medical imaging, 36(9), 1876-1886.
35. Vesal S, Ravikumar N, Maier A (2018) “Skinnet: a deep learning framework for skin lesion segmentation.” In: 2018 IEEE nuclear science symposium and medical imaging conference proceedings (NSS/MIC). IEEE, pp 1–3
36. Bi L, Kim J, Ahn E, Kumar A, Fulham M, Feng D (2017) Dermoscopic image segmentation via multistage fully convolutional networks. IEEE Trans Biomed Eng 64(9):2065–2074
37. Codella NCF, Gutman D, Celebi ME, Helba B, Marchetti MA, Dusza SW, Kalloo A et al. (2018) “Skin lesion analysis toward melanoma detection: a challenge at the 2017 international symposium on biomedical imaging (isbi), hosted by the international skin imaging collaboration (isic).” In: 2018 IEEE 15th international symposium on biomedical imaging (ISBI 2018), pp 168-172.
38. Berseth M (2017) “ISIC 2017-skin lesion analysis towards melanoma detection.” arXiv preprint arXiv :1703.00523

39. Qian C, Jiang H, Liu T (2018) “Skin lesion analysis” ISIC
40. Hao D, Seok JY, Ng D, Yuan NK, Feng M (2018) ISIC Challenge 2018. ISIC
41. Ji Y, Li X, Zhang G, Lin D, Chen H (2018) Automatic skin lesion segmentation by feature aggregation convolutional neural network. ISIC
42. Koohbanani NA, Jahanifar M, Tajeddin NZ, Gooya A (2018) “Leveraging transfer learning for segmenting lesions and their attributes in dermoscopoy images”, ISIC
43. Molina-Moreno M, González-Díaz I, Díaz-de-María F (2018) An elliptical shape-regularized convolutional neural network for skin lesion segmentation. ISIC
44. Xue Y, Gong L, Peng W, Huang X, Zheng Y (2018) Automatic skin lesion analysis with deep networks. ISIC
45. Sorokin A (2018) Lesion analysis and diagnosis with mask-RCNN. ISIC
46. Yang J, Chen W (2018) Skin lesion analysis using deep neural networks. ISIC
47. Dandi CX, Che MC, Jingyuan C, Zhuoran X, Fei W (2018) U-Net ensemble for skin lesion analysis towards melanoma detection. ISIC
48. Yuan Q, Tavildar S (2018) An open solution to ISIC 2018 classification and segmentation challenges. ISIC
49. Xie, F., Yang, J., Liu, J., Jiang, Z., Zheng, Y., & Wang, Y. (2020). Skin lesion segmentation using high-resolution convolutional neural network. Computer methods and programs in biomedicine, 186, 105241.
50. Khan, M. A., Sharif, M. I., Raza, M., Anjum, A., Saba, T., & Shad, S. A. (2022). Skin lesion segmentation and classification: A unified framework of deep neural network features fusion and selection. Expert Systems, 39(7), e12497.
51. Bibi, A., Khan, M. A., Javed, M. Y., Tariq, U., Kang, B. G., Nam, Y., ... & Sakr, R. H. (2022). Skin lesion segmentation and classification using conventional and deep learning-based framework. Computer Mater. Contin, 71, 2477-2495.
52. Phan, T. D. T., Kim, S. H., Yang, H. J., & Lee, G. S. (2021). Skin lesion segmentation by u-net with adaptive skip connection and structural awareness. Applied sciences, 11(10), 4528.
53. Sarker, M. M. K., Rashwan, H. A., Akram, F., Singh, V. K., Banu, S. F., Chowdhury, F. U., ... & Abdel-Nasser, M. (2021). SLSNet: Skin lesion segmentation using a lightweight generative adversarial network. Expert Systems with Applications, 183, 115433.
54. Wu, H., Chen, S., Chen, G., Wang, W., Lei, B., & Wen, Z. (2022). FAT-Net: Feature adaptive transformers for automated skin lesion segmentation. Medical image analysis, 76, 102327.
55. Khan, M. A., Sharif, M., Akram, T., Damaševičius, R., & Maskeliūnas, R. (2021). Skin lesion segmentation and multiclass classification using deep learning features and improved moth flame optimization. Diagnostics, 11(5), 811.
56. Hosny, K. M., Elshora, D., Mohamed, E. R., Vrochidou, E., & Papakostas, G. A. (2023). Deep Learning and Optimization-Based Methods for Skin Lesions Segmentation: A Review. IEEE Access.
57. Khouloud, S., Ahlem, M., Fadel, T., & Amel, S. (2022). W-net and inception residual network for skin lesion segmentation and classification. Applied Intelligence, 1-19.
58. Basak, H., Kundu, R., & Sarkar, R. (2022). MFSNet: A multi focus segmentation network for skin lesion segmentation. Pattern Recognition, 128, 108673.