Received 23 July 2023, accepted 7 August 2023, date of publication 10 August 2023, date of current version 16 August 2023.
Digital Object Identifier 10.1109/ACCESS.2023.3303961

TOPICAL REVIEW

Deep Learning and Optimization-Based Methods for Skin Lesions Segmentation: A Review

KHALID M. HOSNY[1], (Senior Member, IEEE), DOAA ELSHOURA[1], EHAB R. MOHAMED[1], ELENI VROCHIDOU[2], AND GEORGE A. PAPAKOSTAS[2]
[1]Department of Information Technology, Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Egypt
[2]MLV Research Group, Department of Computer Science, International Hellenic University, 65404 Kavala, Greece

Corresponding author: George A. Papakostas (gpapak@cs.ihu.gr)

This work was supported in part by the Hellenic Academic Libraries Link (HEAL-Link) Greece.

ABSTRACT Skin cancer is a senior public health issue that could profit from computer-aided diagnosis to decrease the encumbrance of this widespread disease. Researchers have been more motivated to develop computer-aided diagnosis systems because visual examination wastes time. The initial stage in skin lesion analysis is skin lesion segmentation, which might assist in the following categorization task. It is a difficult task because sometimes the whole lesion might be the same colors, and the borders of pigment regions can be foggy. Several studies have effectively handled skin lesion segmentation; nevertheless, developing new methodologies to improve efficiency is necessary. This work thoroughly analyzes the most advanced algorithms and methods for skin lesion segmentation. The review begins with traditional segmentation techniques, followed by a brief review of skin lesion segmentation using deep learning and optimization techniques. The main objective of this work is to highlight the strengths and weaknesses of a wide range of algorithms. Additionally, it examines various commonly used datasets for skin lesions and the metrics used to evaluate the performance of these techniques.

INDEX TERMS Skin melanoma, pre-processing, segmentation, deep learning, optimization.

I. INTRODUCTION

Dermatologists can now identify and classify skin lesions more easily because of advancements in medical image processing [1], [2]. Pigmented skin lesions, categorized as benign or malignant, are mostly brought on by aberrant cell production in some areas. Since benign skin lesions do not spread to neighboring tissues, they behave more orderly than malignant lesions. Nevi are benign lesions, including melanocytic, halo, blue, spitz, and dysplastic nevi (Fig. 1(a)) and seborrheic keratosis (Fig. 1(b)). Malignant lesions have cells that divide quickly and have the potential to spread to other body regions. These cells do not often perish, as happens with regular cells.

The two primary categories for skin cancer are melanoma (Fig. 1(c)) and non-melanoma (Fig.1 (d)). Melanoma is an aggressive, rare, and lethal form of skin cancer. Examples of non-melanoma include basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and sebaceous gland carcinoma (SGC). They are the most prevalent type of skin cancer. Furthermore, because these cancers have fewer chances of spreading (metastasizing) to a different body area than melanoma, they have a greater chance of being cured. Melanoma is the deadliest skin cancer, with the greatest fatality rate due to its high metastasis rates [3]. Compared to melanoma cancers, non-melanoma cancers are simpler to cure.

Age plays a critical part in melanoma risk. The average age of persons who receive a diagnosis is 65 years old. Men are twice as likely as women to acquire melanoma skin cancer. According to some recent estimates, the number of melanoma skin cancer fatalities in the United States in 2023 will be significantly higher for men than for women [4].

Lately, there has been a lot of attention on developing computer-aided diagnostic (CAD) systems for identifying and assessing pigmented skin lesions from images [5], [6], [7], which may help dermatologists halt the growth of malignant lesions. Furthermore, early detection of malignant

The associate editor coordinating the review of this manuscript and approving it for publication was Daniel Augusto Ribeiro Chaves.

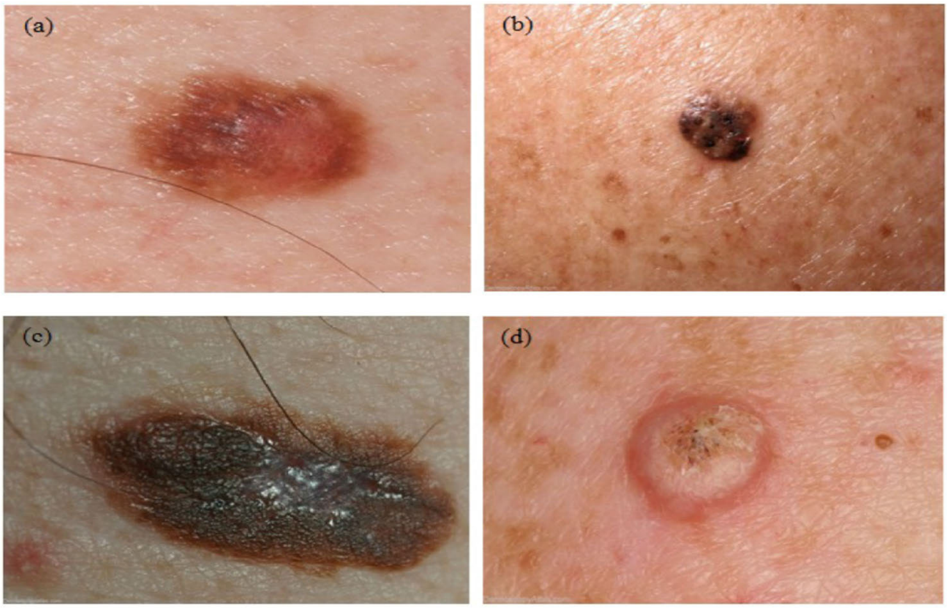


FIGURE 1. Skin lesions examples: (a) dysplastic nevus, (b) seborrheic keratosis, (c) melanoma, and (d) non-melanoma [1].

lesions might increase the likelihood of a patient's recovery and create better circumstances for effective treatment.

On the other hand, the image segmentation step of CAD systems also attracts a lot of attention. The lesion under examination may be more accurately represented, and its features can be extracted. On this topic, a significant amount of research has been done. As a result, collecting, analyzing, classifying, and evaluating the existing research findings is critical.

The structure of the review paper is as follows. Section II discusses image acquisition and available datasets. Section III outlines various pre-processing methods for skin lesions. The methodology for effective analysis of deep learning techniques and optimization methods for skin cancer (SC) segmentation is presented in Section IV. Section V demonstrates the widely used criteria for evaluating various image segmentation techniques. Sections VI and VII contain the discussion and conclusions, respectively.

II. IMAGE ACQUISITION AND AVAILABLE DATASETS FOR SKIN CANCER

Dermatologists have employed several non-invasive imaging techniques to help in skin lesion diagnosis. Imaging techniques include dermatoscopy, confocal scanning laser microscopy (CSLM), photography, ultrasound, magnetic resonance imaging (MRI), optical coherence tomography (OCT), and spectroscopic imaging [8], [9]. Clinical images are typically referred to as microscopic images [10], [11], and images are obtained using Epiluminescence microscopy (ELM), often known as dermoscopy or dermatoscopy images [12], [13], [14], [15]. Fig. 2 provides illustrations of dermoscopy and macroscopic images [1].

Clinical images are typically captured using general image cameras or digital video equipment. However, the imaging conditions in clinical settings can be unpredictable, with images taken from varying distances and lighting conditions. Moreover, these images may suffer from poor resolution, which makes it challenging to identify minor lesions or abnormalities. These challenges can impact the accuracy of clinical diagnoses and highlight the need for advanced imaging techniques and equipment that can reliably capture high-quality images in diverse conditions. The presence of artifacts in clinical images, such as reflections, shadows, skin lines, and hair, can make it difficult to analyze skin lesions accurately. Usually, Epiluminescence microscopy (ELM) is a non-invasive image acquisition technique in which the lesion is immersed in oil. After that, the images are captured by a dermatoscopy device (with a certain camera). This technique makes it easier to see the skin's surface pigmentation pattern. The non-polarized imaging modality can occasionally be attributed to oil immersion. Transillumination and Cross-polarization are two other ELM techniques that can be used. These modalities use a nevoscope device to capture the images. The transillumination modality accentuates the blood flow and beneath vascular, whereas both modalities emphasize surface pigmentation. Air bubbles and hairs must be removed from the images to recognize skin lesions better.

The datasets that are most often used in this research area are presented in this section. Several freely available, unrestricted online datasets, including DermaIS, DermQuest, and the ISIC for 2016, 2017, 2018, 2019, 2020, PH2, and Dermofit, were used. The method for recognizing skin cancer on microscopic images was developed and tested [16].

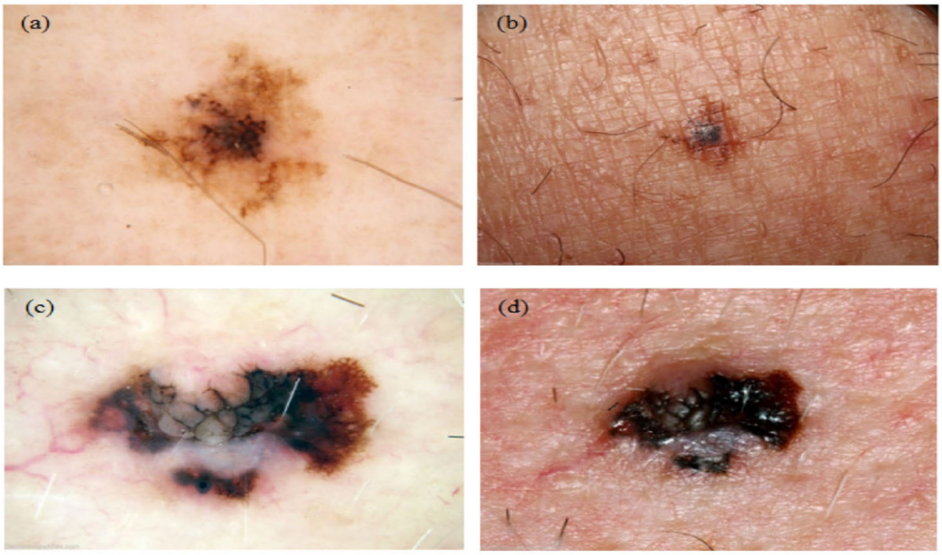


FIGURE 2. Illustrations of dermoscopy (a and c) and macroscopy (b and d).

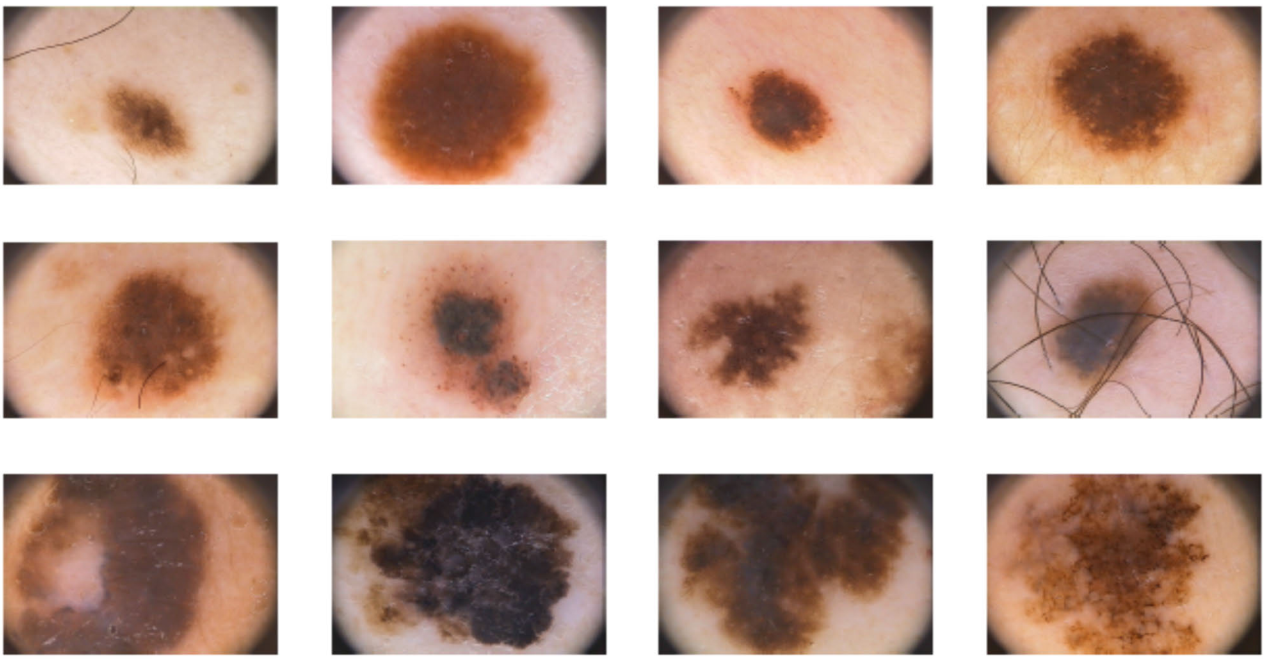


FIGURE 3. Common nevi (1st row), Atypical nevi (2nd row), and Melanomas (3rd row) from the PH2.

An overview of the publicly available dermatological datasets is presented in Table 1.

DermIS is called the "Dermatology Information System." Nevus and melanoma are the two categories into which this dataset is separated. There were 69 images, 26 nevi, and 43 melanomas [17]. DermQuest has 137 images, Consisting of two groups, melanoma 76 and nevus 61 images, respectively [18].

The PH2 dataset is called "Pedro Hispano Hospital." Melanoma, normal nevus, and atypical nevus are the three images in this dataset, with 40, 80, and 80 images in each group. The dataset includes ground truth images and a medical explanation for each image based on the medical segmentation of the tested region. A skilled dermatologist was used to apply the manual partitions of the lesion's area and dermoscopic norm (ground truth) [19]. The skin colors characterized in this dataset may range from white to creamy white. The images were carefully selected, as seen in Fig. 3, taking into account their resolution, quality, and dermoscopic features.

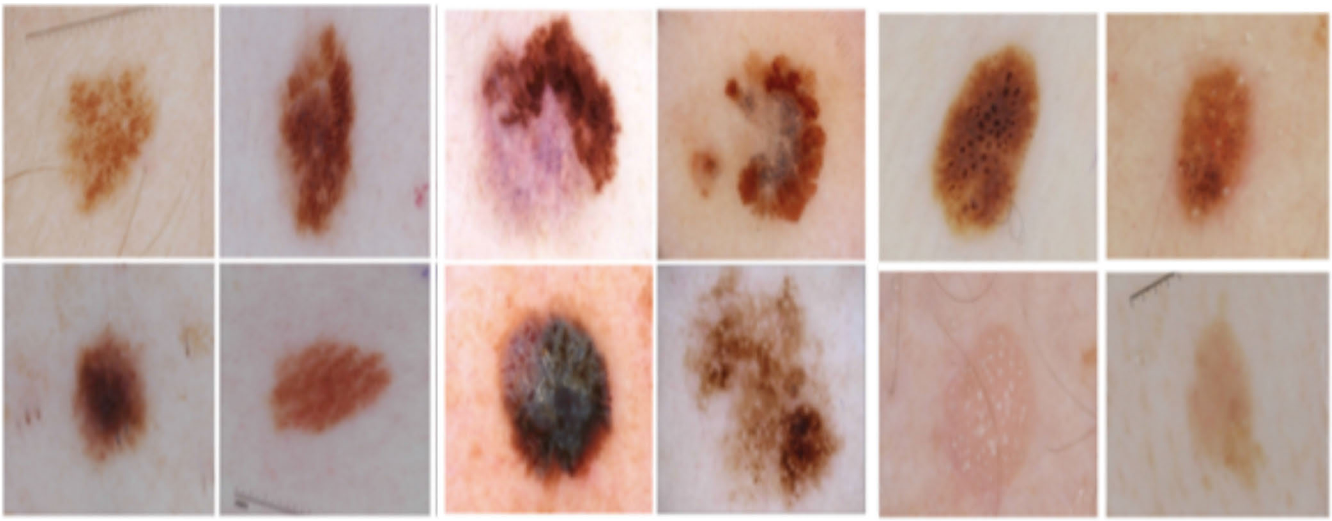


FIGURE 4. Examples of various skin lesions from the ISIC 2017.

TABLE 1. Summary of skin lesions datasets.

	DERMIS	DERMQUEST	PH2	ISIC 2016	ISIC 2017	ISIC20 2018	ISIC 2019	ISIC 2020	DERMOFIT	EDRA
Nevus or Atypical Nevus	26	61	80	726	1372	6705	12875	46	331	560
Common Nevus	-	-	80	-	-	-	-	5193	-	55
Melanoma	43	76	40	173	374	1113	4522	584	76	196
Seborrheic Keratosis	-	-	-	-	254	1099	2624	135	257	45
Basal Cell Carcinoma	-	-	-	-	-	514	3323	7	239	42
Dermatofibroma	-	-	-	-	-	115	239	-	65	20
Actinic Keratosis	-	-	-	-	-	327	867	37	45	-
Vascular Lesion or Hemangioma	-	-	-	-	-	142	253	-	97	29
Squamous Cell Carcinoma	-	-	-	-	-	-	628	-	88	-
Intraepithelial Carcinoma	-	-	-	-	-	-	-	-	78	64
Pyogenic Granuloma	-	-	-	-	-	-	-	-	24	-
Other/Unknown	-	-	-	-	-	-	-	27124	-	-
Total number of images	69	137	200	899	2000	10015	25331	33126	1300	1011

The ISIC 2016 "International Skin Imaging Collaboration," proposed for the ISBI challenge, contains 900 training images and consists of two classes in the training dataset. Melanoma and benign classes comprise 173 and 727 dermoscopic images, respectively [20]. The ISIC 2017 dataset proposed for the "ISBI 2017 Challenge" includes 2,000 training images divided into three classes, represented by 374, 254, and 1372, respectively. Also includes a validation dataset that contains 150 unique images, and the test dataset unthinkingly held out 600 images [21]. Examples of various ISIC 2017 skin lesions are shown in Fig. 4.

The ISIC 2018 dataset, HAM10000 (Human Against Machine with 10,000 Training Images), consists of 10,015 training and 1,512 testing images. Seven classes are represented in the training dataset: Actinic Keratosis (AKIEC), BCC, Benign Keratosis (BKL), Melanoma (MEL), Dermatofibroma (DF), Melanocytic Nevus (NV), and Vascular Lesion (VASC). There are various numbers of images in each of these classes. There are 1,113 in the MEL, 6,705 in the NV, 514 in the BCC, 327 in the AKIEC, 1,099 in the BKL, 115 in the DF, and 142 in the VASC. One of the most challenging problems in this dataset is classifying different images into seven groups [22], [23].

The ISIC 2019 dataset consists of eight classes plus a class for outlier images since each class has an unequal number of images. These classes include 25,331 images, 12,875 from NV, 4,522 from MEL, 3,323 from BCC, 867 from AKIEC, 2,624 from BKL, 239 from DF, 628 from SCC, and 253 from VASC [24]. Fig. 5 shows the many forms of skin cancer. The ISIC 2020 Challenge dataset includes 33,126 dermoscopic training images of distinct benign and malignant skin lesions from more than 2,000 patients. Each image is connected with one of these individuals using a unique patient identifier. The dataset's images were divided into nine classes and one unknown data image class [25].

The Dermofit Image dataset comprises 1,300 high-quality focal images captured under standardized conditions with internal color standards. In this dataset, there are ten different

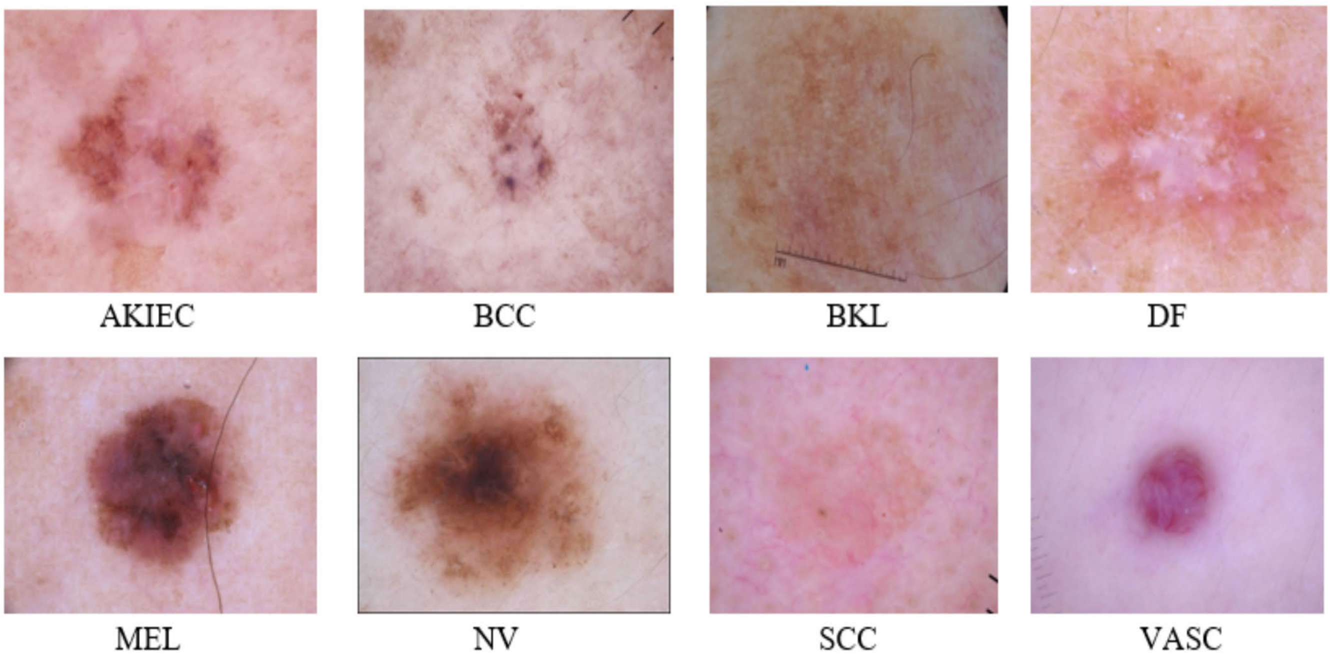


FIGURE 5. Examples of various skin lesions from ISIC 2019.

types of lesions. These classes include images for nevus, MEL, seborrheic keratosis, BCC, DF, AKIES, hemangioma, SCC, intraepithelial carcinoma, and pyrogenic granuloma, totaling 331, 76, 257, 239, 65, 45, 97, 88, 78, and 24 [26].

The EDRA "Interactive Atlas of Dermoscopy" dataset has 20 labels with various kinds of melanoma, including BCC, blue nevus, Clark's nevus, congenital nevus, dermal nevus, combined nevus, DF, lentigo, melanosis, Reed nevus, recurrent nevus, VASC [27]

III. PRE-PROCESSING METHODS FOR SKIN LESIONS SEGMENTATION

The pre-processing step is an optional but significant step implemented to provide better visual information for the human viewers or to get improved input for the automated image processing algorithms. Pre-processing eliminates unwanted artifacts such as hair, blood vessels, color charts, ruler lines, marker inks, vignettes, noise, uneven lighting, and specular highlights. Without this step, the exact segmentation of the image may not be easy. Most currently used segmentation methods rely heavily on several pre-processing methods to avoid the consequences of undesirable artifacts that could impair accurate skin lesion segmentation [28]. Artifact removal methods are based on thresholding [29], [30], filtering [30], morphology [31], [32], and DullRazor [28], [33], [34], [35].

Similarly, image enhancement pre-processing techniques are frequently used to improve dermoscopic images' low contrast and non-uniform illumination. These enhancement methods depend on filtering [29], [36], [37], [38], contrast adjustment [30], [36], adaptive histogram equalization [32], [39], and contrast-limited adaptive histogram equalization (CLAHE) [38], [40], [41], [42]. Studies have shown that the best method for pre-processing medical images is CLAHE among general enhancement methods [38].

TABLE 2. Image pre-processing methods utilized in the segmentation of skin lesions.

Artifacts removal	Image enhancement	Ref.
Deep learning method	-	[28]
Thresholding	Median filter	[27]
Morphological operations	Unsharp filtering	[31]
Morphological operations	Histogram equalization	[32]
DullRazor	Median filter	[35]
DullRazor	Noise filtering with intensity adjustment	[36]
Threshold decomposition	Homomorphic filtering.	[37]
-	Contrast-limited adaptive histogram equalization	[41], [42]
Averaging filter	Contrast enhancement	[43]
-	Adaptive histogram equalization	[39]
-	Adaptive gamma correction	[44]
DullRazor	Global-local Contrast stretching	[45]
A fast-line detector	Gamma correction	[46]
Frangi Vesselness filter	Contrast-limited adaptive histogram equalization.	[40]
Enhanced DullRazor	Top–bottom filtering, Log transformation, and Contrast stretching.	[47]
-	Z-score transformation	[48]
Multi-scale decomposition	-	[49]
DullRazor	-	[50]
-	Standard deviation-based normalization and Mean subtraction	[51]

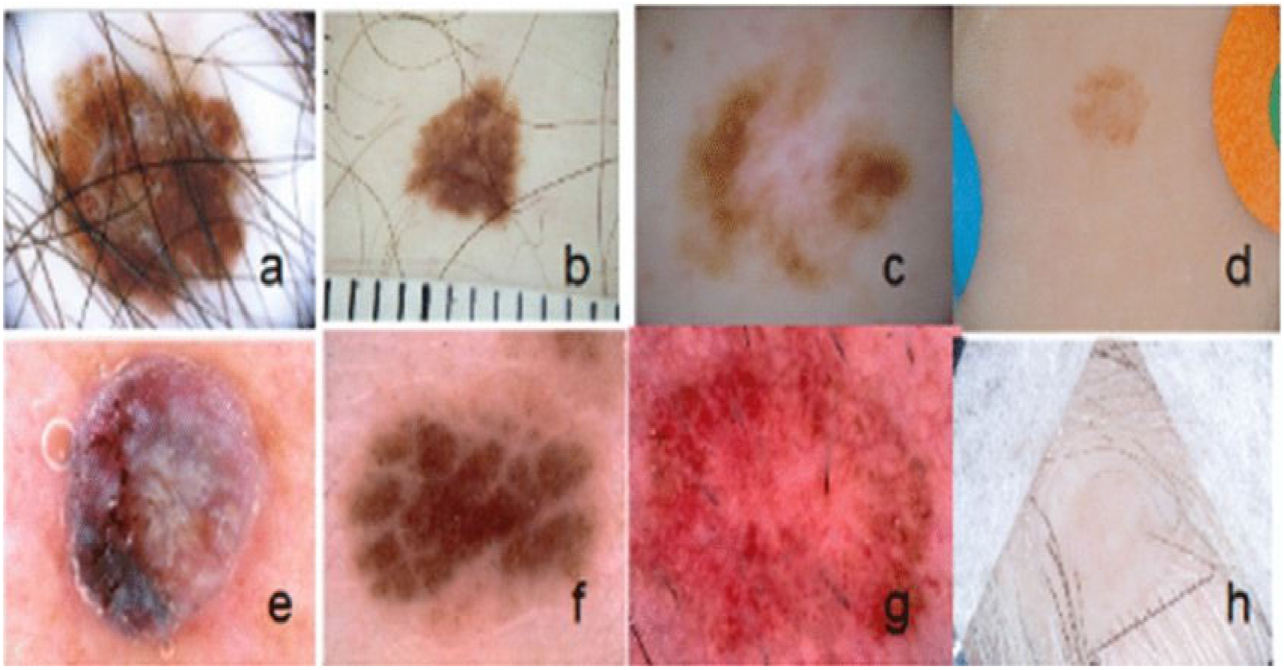


FIGURE 6. Challenges in identifying skin lesions: (a) hair artifact, (b) ruler mark artifact, (c) low Contrast, (d) color illumination, (e) bubbles, (f) irregular boundaries, (g) blood vessels, (h) frame artifact.

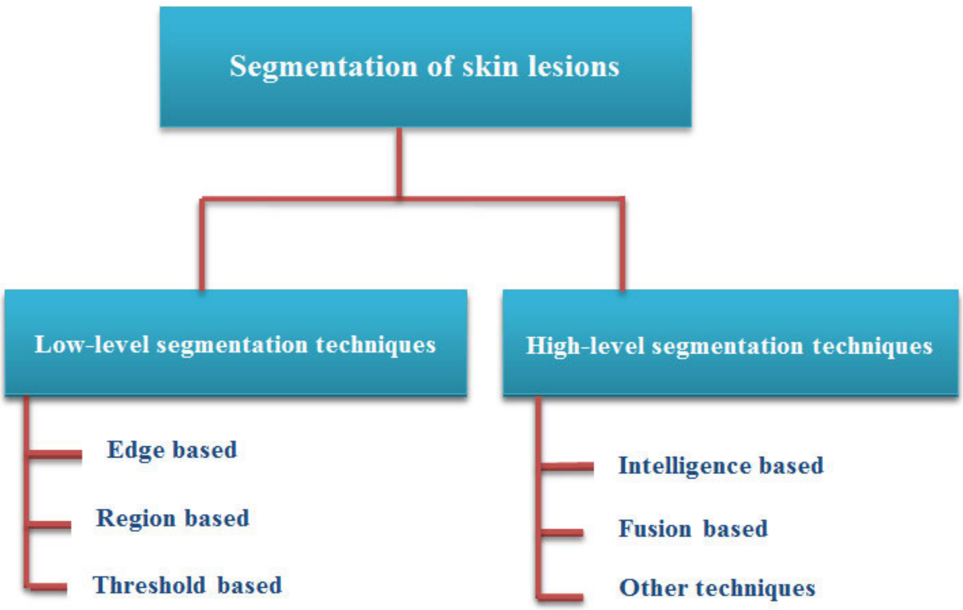


FIGURE 7. Techniques for pigmented skin lesions image segmentation.

The artifact removal and image enhancement methods are frequently carried out before the segmentation, and post-processing methods are applied to remove the remaining noise. Various pre-processing methods that the relevant researchers utilized for skin lesion segmentation are discussed in Table 2.

IV. SKIN LESIONS IMAGE SEGMENTATION

In medical image analysis, segmentation is crucial, obtaining an image's region of interest (ROI) under analysis. Generally, the segmentation process alludes to dividing an image into distinct regions containing each pixel with kindred attributes [52]. Accurate skin lesion segmentation is difficult because

TABLE 3. Comparison between conventional methods and intelligence-based methods for skin lesion segmentation.

Segmentation Techniques	Description	Advantages	Disadvantages
Edge-based	Depending on the magnitude of the gradient used to find the edges of the ROI, it may be possible to determine changes in the intensity of the pixels in a segmentable image. There are several instances of edge detectors, including the Prewitt, Sobel, Roberts, Laplacian, and Canny operators [54].	Typically simpler. Edges are crucial components in an image to separate regions combination of results may often be a good idea.	Detection of an edge where no actual border exists. Possible generation of double edges. Extremely sensitive to image noise.
Region-based segmentation	Depending on their properties, images are divided into regions or collections of related pixels. Examples: region-growing [55], splitting and merging [56], and the Mumford–Shah method [57].	More information is available to characterize your region since regions cover more pixels than edges. You could use texture to detect a region; however, dealing with edges makes this difficult.	Noise levels might also influence the results, generating two edges simultaneously and inaccurate detection.
Threshold-based segmentation	Depending on the image, a histogram and known as point- or pixel-based. Examples: Otsu's, Adaptive thresholding, Renyi's entropy, etc. [58], [59].	Its low storage needs, speed, accuracy, and ease of use.	There is no significant grayscale difference or a large overlap of the image's gray values.
Intelligence-based Segmentation - ANN models - Genetic Algorithms - Fuzzy C-means (FCM).	Depending on the artificial intelligence approach is the widest approach in the automated dermatology field [60].	Fault tolerance, Flexibility, fast computational time during the inference stage, and Maximum performance.	This technique must be trained on a sizable amount of image data. Due to the intricacy of skin lesions, acquiring prior information on the number of clusters is challenging. Requires more expensive computation than other methods and huge amounts of memory storage.
Deep Learning: Fully Convolutional Neural Network (FCN) - U-Net - Deep Residual Network - SegNet.	Deep learning can learn optimal hierarchical features from the raw images directly rather than hand-crafted features by the network designer. [61].	Utilize end-to-end learning, where raw data is transformed into a network, and then the network learns for optimal task automation.	
Fusion-based segmentation	Combining two or more techniques to create a sophisticated segmentation [62].	By combining several thresholding techniques, you may get the optimal thresholding.	More complex and needs higher computational resources.

of the various image types and sources that might influence skin color appearance. These are illustrated in Fig. 6.

The following list includes some of the most typical difficulties encountered while segmenting skin lesions from images:

- *Unclear boundaries:*
  Sometimes, the skin lesion image and its boundaries become unclear. Many techniques are difficult in such situations to identify and define lesion boundaries.
- *Illumination variations:*
  Light in every place is not the same. The appearance of the same lesion can change depending on the type of light system used. In clinical imaging, ensuring enough light of the right intensity, brightness, and color.
- *Unwanted data and artifacts:*
  Undesirable features like hair, moles, skin burns, bubbles, blood vessels, or wrinkles might make it difficult to determine the lesion's boundaries and result in unwanted or unsuitable lesions that serve no useful purpose.
- *Image size and shape:*
  The variability in the form and size of the lesion boundary makes the segmentation more challenging.

TABLE 4. Research related to skin lesions segmentation.

Methods: Broad categorization	Methods: Specific categorization	Dataset	Ref.
Edge-based	Edge detectors	---	[54]
		320 images from the skin lesion dataset	[63]
		---	[64]
Region-based	Region growth, Statistical region merging, Iterative stochastic region merging	ISIC2017 (50 images for training &500 for testing)	[55]
		---	[56]
		ISIC(60 images) (23 benign& 37 malignant)	[57]
		---	[65]
		ISIC2017 (1126 for training & 520 for testing)	[66]
		ISIC2017&PH2	[67]
		PH2& ISIC (200 dermoscopy & 2000 Kaggle's skin lesion images)	[68]
		PH2& ISIC2018 (200 & 2594 dermoscopic images)	[69]
		ISIC2018	[70]
Thresholding-based	Otsu's thresholding, Adaptive thresholding, Iterative thresholding	---	[58], [59], [71]
		(15 dermoscopy of melanoma images)	[72]
		ISIC2017 (600 high-quality color images)	[73]
		PH2& ISIC2017 (RGB dermoscopic images)	[74]
		Prof. Ganster kindly provided the skin database at the Vienna Hospital. 1041 images(972 nevus &69 malignant)	[60]
Intelligence-based (AI-based)	Neural networks, Evolutionary computation, Fuzzy logic	---	[61],[75]
		ISIC2018 (2594 for training &1000 for testing dermoscopic images)	[76]
		ISIC2016 (900 for training, 379 for testing) ISIC2017(2000 for training, 150 for validation, 600 for testing) ISIC2018(10015 for training)	[77]

TABLE 4. ***(Continued.)*** **Research related to skin lesions segmentation.**

Active contour-based	K-means clustering, Gradient vector flow, Region-based active, Contour algorithm, Active contour without edges	ISIC(318# of images) (21 Angioma, 46 Nevus,41 Lentigo NOS,68 Solar Lentigo,51 Melanoma,54 Seborrheic Keratosis,37 Basal Cell Carcinoma)	[78]
		---	[79]
		ISIC2016 (900 for training, 380 for testing) ISIC2017(2000 for training, 150 for validation, 600 for testing) PH2(200)	[80]
		206 images (supplied by Vision and Image Processing Lab, University of Waterloo) 119 melanoma, 87 non-melanoma ISIC (2594+2000+900) images.	[81]
Other methods	Chan-Vese, Dictionary-based method, Hill-climbing, Dynamic programming	Different skin lesions (Melanoma, Benign, Malignant, and ISIC vascular lesions)	[82]
		PH2(200 dermoscopic images)	[83]
		ISIC2016	[84]
		ISCI2016 (1279 images (273 melanoma and 1006 benign), 900 images for training & 350 for testing. ISCI 2017 (2750 images (517 melanoma and 2233 benign) 2000 training&750 testing.	[62]
		PH2 (200) 200 images (116 melanoma& 84 non-melanoma)	[85]
		---	[86]
		ISIC2017(2750 dermoscopic) 2000 images (1372 benign, 254 SK(seborrhoeic keratosis), and 374 melanoma) for the training set, 150 images (78 benign, 42 SK, and 30 melanoma) for validation, and 600 images (393 benign, 90 SK, and 117 melanoma) for testing	[87]
		ISIC2018 (10015 dermoscopic images)	[88]

- *Imaging conditions:*
  Imaging conditions indicate the kind of camera used. Changing the camera and resolution can significantly affect the state of the image.
- *Aging:*
  Age-related skin changes include wrinkles, stretch marks, fading of skin color, and other physical traits, including skin texture and smoothness.
- *Background image:*
  Lesion segmentation and feature recognition benefit greatly from clean backgrounds, whereas complex backgrounds make the segmentation task difficult.
- *Race and community:*
  This factor has a bigger influence on skin color. Compared to persons who live in tropical climate regions and warmer temperature conditions, those who live in

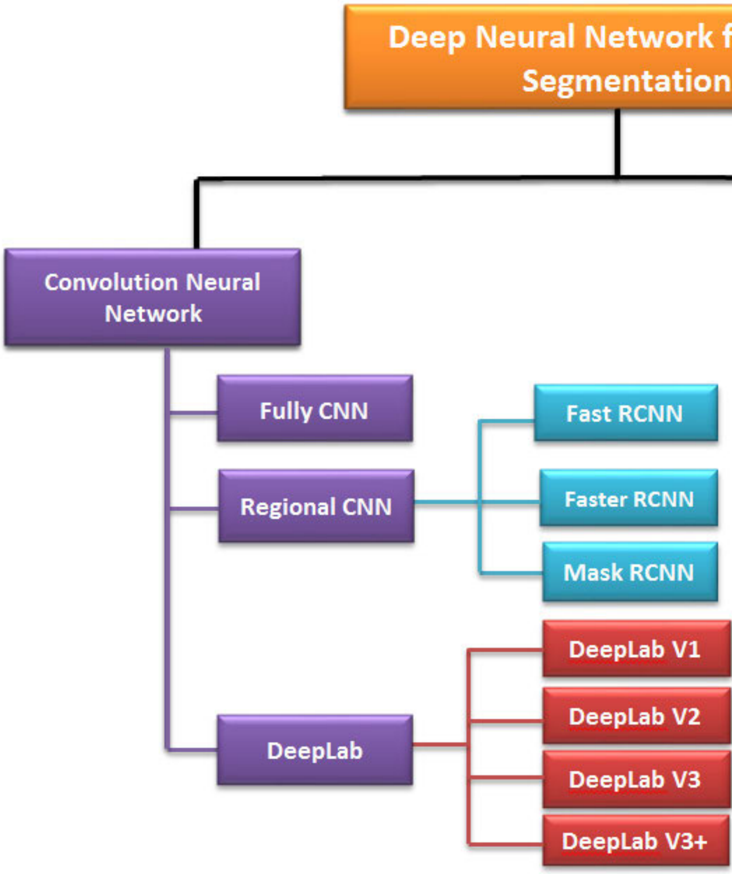


FIGURE 8. Different deep neural network architectures for image segmentation.

colder climates are more likely to have their melanoma diagnosed earlier.

Nevertheless, as previously stated, pre-processing methods may be applied to the original images to facilitate the segmentation process and improve the resultant accuracy [53].

In this section, we show several methods that are often used in literature for pigmented skin lesion segmentation, such as edge-, region-, thresholding-based methods, and methods dependent on artificial intelligence (AI) and active contours as shown in Fig. 7. Table 3 compares several segmentation techniques, highlighting their advantages and disadvantages. Table 4 shows some of the research that has been accomplished relevant to skin lesion segmentation.

A. DEEP LEARNING TECHNIQUES FOR SKIN LESION SEGMENTATION

Recently, several studies explored how deep learning models may be used to segment skin lesions. Deep neural networks play a crucial role in diagnosing skin lesions. They are composed of several connected nodes which work cooperatively to solve a specific issue. Their structure is identical to the human brain in terms of neuronal interconnectedness. DL and neural networks (NN) have gained momentum in present-day scientific research since they can learn from the context. A deep learning technique builds an artificial neural network using a variety of layers. An artificial neural network (ANN) comprises the input, hidden, and output layers [89]. The network's input layer receives the signal. An output layer makes decisions relating to the input. Between the input and output layers, many hidden layers accomplish computations. Deep Learning allows computational models of multiple processing layers to learn and represent data with multiple levels of abstraction. DL is a rich family of methods comprising neural networks, hierarchical probabilistic models, and a variety of unsupervised and supervised feature learning algorithms. This section overviews several deep-learning methods for image segmentation.

Researchers have proposed various deep-learning models that achieve excellent skin lesion segmentation performance [90]. Many deep learning network architectures frequently used for image segmentation may be classified as demonstrated in Fig. 8. Each technique has strengths and weaknesses. A concise comparison of various deep-learning image segmentation algorithms is provided in Table 5. Here, we have shown the methods used in research papers and information about the datasets authors used in their papers.

The following papers have been gathered from different sources, such as Google Scholar, IEEE Xplore,

TABLE 5. Deep learning algorithms used for image segmentation.

Deep Learning Algorithms	Description	Advantages	Disadvantages
CNN	It consists of convolutional layers pooling and fully connected layers [110].	Uncomplicated. It includes supplying the network with an image's segments as input to label the pixels.	It is unable to handle different input sizes. Having a fixed output layer size makes segmentation tasks difficult.
FCN	The fully convolutional layers substitute all of CNN's fully connected layers [111].	The model produces a spatial segmentation map instead of classification scores.	It requires a lot of training to achieve good performance.
U-Net	It predicts a segmentation map by merging location information from the down and contextual information from the up-sampling path [112], [113].	It can effectively segment images by a limited number of labeled image training.	It can easily overfit on small datasets, leading to poor generalization performance.
V-Net	Each stage is convolved by volumetric kernels of size 5x5x5 [114].	It can be used to segment 3D data.	The resolution of the data is reduced.
RCNN	It extracts 2,000 regions (region proposals) from the image using a selective search method [115].	It predicts whether an object will be in the proposal's region. Additionally, it expects four offset values to improve the bounding box's accuracy.	Training the network to classify 2,000 region proposals per image takes time. The Selective search method is static. Real-time implementation is not possible.
Fast R-CNN	It utilizes a selective search method that takes all images as input and region proposals for its CNN architecture in a one-forward propagation [116].	Compared to R-CNN, it increases mean average precision (MAP).	Because of the selective search region proposal generation method, there is a long computation time.
Faster RCNN	It makes utilization of the regional proposal network [117].	It uses a novel region proposal network (RPN) for generating region proposals, which saves time compared to traditional algorithms like Selective Search.	It still uses the Selective Search Algorithm, a slow and time-consuming process. It takes around 2 seconds per image to detect objects, which sometimes does not work properly with large real-life datasets.
Mask RCNN	Three outputs are generated for each object in the image: its class, bounding box coordinates, and object mask. [118].	Easy and adaptable technique. The most advanced method is currently available for image segmentation.	A lot of time is spent on training.
DeepLabv1	To separate the features from an image, it uses atrous convolution. A conditional random field (CRF) also collects tiny details [119].	High-speed results by atrous convolution. Merging DCNNs and probabilistic graphical models enhances the localization of object boundaries.	CRF use slows the algorithm.
DeepLabv2	It uses atrous spatial pyramid pooling (ASPP) to combine various atrous convolutions applied to the input feature	Adequately segments objects at multiple scales.	Fine object boundaries are difficult to capture.

TABLE 5. Deep learning algorithms used for image segmentation.

	map at various sampling rates [120].		
DeepLabv3	Sharper object boundaries are captured via atrous separable convolution [121].	The ability to pick up larger context information due to atrous convolutions and extract features at different scales.	For object boundaries, additional work must be done.
DeepLabv3+	It expands DeepLabv3 by adding a decoder module to improve segmentation outcomes around the objects' borders [122].	Compared to deepLabv3, there is better segmentation performance.	It is a sizable model with many parameters that need to be trained. So, Large GPU memory is required.

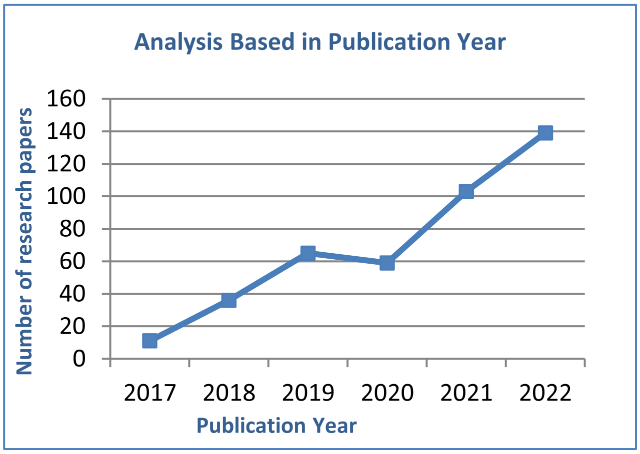


FIGURE 9. The number of research papers in deep learning for skin lesion segmentation.

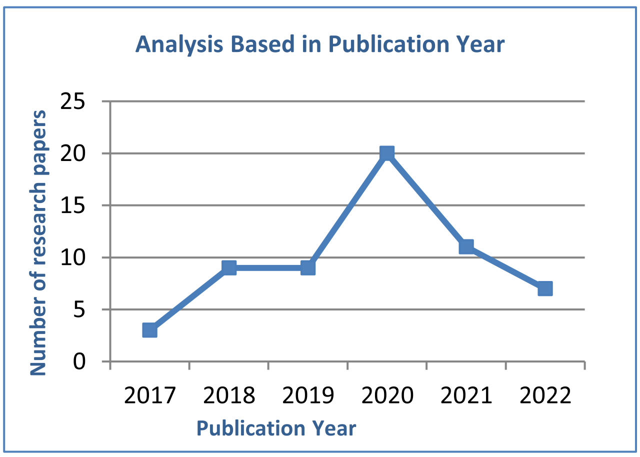


FIGURE 10. The number of research papers in optimization for skin lesion segmentation.

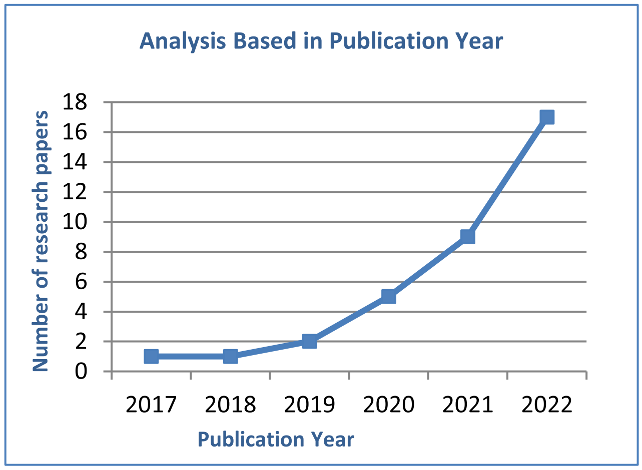


FIGURE 11. The number of research papers in optimized deep learning for skin lesion segmentation.

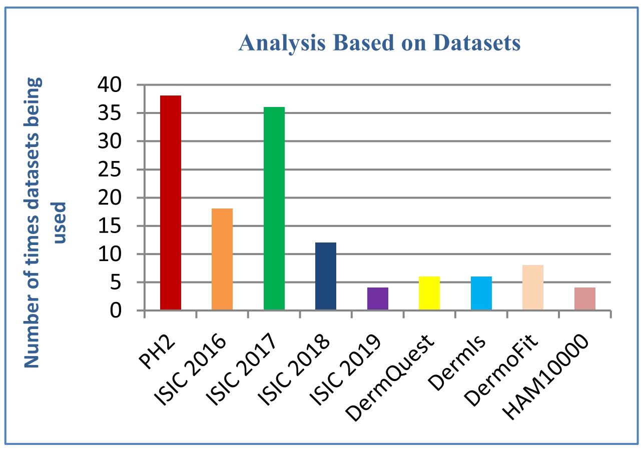


FIGURE 12. Analysis based on datasets.

ScienceDirect, and SpringerLink. Occasionally, the finding also suggests some authors have used more than one dataset, which is also mentioned below. This survey also shows the authors' names and models or segmentation techniques.

Table 6 discusses various deep-learning methods the related researchers used to segment skin lesion images.

B. OPTIMIZATION TECHNIQUES FOR SKIN LESION SEGMENTATION

The optimization process identifies the best possible solution(s) to a certain issue. Optimization problem examples involve determining the shortest path to a destination or planning tasks to decrease spent time or consumed. Optimization

TABLE 6. Deep learning algorithms used for skin lesions segmentation.

Author	Year	Methods	Dataset name	No. of tested images
Lin BS., et al. [122]	2017	U-Net and C-Means Clustering-based approach	ISIC2017	2000
Bozorgtabar B. et al. [123]	2017	Deep Convolutional Networks guided by local unsupervised learning	ISBI 2016	1,279
Izadi S. et al. [124]	2018	Generative adversarial networks GAN (FCNN+ CNN)	DermoFit	1,300
Mirikharaji Z, Hamarneh G. [125]	2018	Fully convolutional network (FCN)	ISBI2017	2,750
Nida N. et al. [31]	2019	RCNN and FCM clustering	ISIC-2016	1,279
Ünver H.M. and Ayan E. [33]	2019	Combining the GrabCut algorithm with the You Only Look Once (YOLO) deep convolutional neural network.	PH2, ISBI - 2017	2,950
Goyal M., et al. [126]	2019	Fully automated deep learning ensemble methods depend on Mask R-CNN and DeeplabV3+methods.	ISIC-2017, PH2	2,950
Xie F. et al. [127]	2020	Proposed a novel CNN (high-resolution convolutional neural network)	ISIC-2016, PH2	1,479
Banerjee S, et al. [128]	2020	deep learning-based 'You Only Look Once (YOLO)' algorithm	ISIC 2017, ISIC 2019, PH2	20,250
Kaymak R., et al. [129]	2020	Automatic semantics uses FCN-AlexNet, FCN-8s, FCN-16s, and FCN-32s.	ISIC 2017	2,750
Zafar K., Gilani S.O. [130]	2020	Combines two architectures, U-Net with ResNet, collectively called Res-Unet.	ISIC 2017, PH2	950
Öztürk Ş, et al [131]	2020	Improved fully convolutional network(IFCN)	ISIC 2017, PH2	2,950
Al-Masni MA, et al [132]	2020	Deep learning full resolution convolutional network (FRCN)	ISIC 2016,2017,2018	11,720
Liu L., Tsui Y.Y., Mandal M. [133]	2021	A novel CNN architecture using auxiliary information	ISBI 2017	2,750
Mirikharaji Z., et al. [134]	2021	An ensemble of Bayesian fully convolutional networks (FCNs)	ISIC, PH2, DermoFit	3,500
Anand V., et al. [135]	2022	A modified U-Net architecture	PH2	200
Akyel C., et al. [136]	2022	LinkNet-B7	ISIC2018, PH2	13,200
Alahmadi M.D. [137]	2022	Multi-Scale Attention U-Net (MSAU-Net)	ISIC 2017, ISIC2018, PH2	4,794
Zhao C. et al. [138]	2022	An improved model based on U-Net++	ISIC2018	2,594
Mustapha A, et al.[139]	2023	Residual Full Convolutional Network (ResFCNET)	ISBI 2016, ISBI 2017	3,879

TABLE 7. Comparison of different optimization techniques for image segmentation.

Optimization Techniques	Advantages	Disadvantages	Ref.
Particle Swarm Optimization (PSO)	Acceptable for multi-objective and constraint handling. Applicable to situations with a fuzzy nature.	Unsuitable for non-coordinate systems and scattering problems. Suffers from partial optimism.	[94]
Cuckoo search (CS)	Higher accuracy and convergence rate. Decreases errors and keeps an algorithm away from local minima. Suitable for problems involving unconstrained Optimization.	Generates uncertainty in optimal values.	[95]
Ant Colony Optimization (ACO)	Suitable for problems that require fragile results. Prevents convergence to a local optimum Inherent Parallelism. Associated with problems where the source and destination are specified and predetermined.	In Contrast to theory, research is experimental. Convergence time is uncertain.	[96]
Gray Wolf Optimization (GWO)	Fewer parameters, simple principles, and implemented easily.	slow convergence speed, low solution accuracy, and easy falling into the local optimum	[97]
Firefly optimization	Deals with a combinatorial optimization problem. Fast convergence speed. High inner parallelism. The ability to automatically sub-division.	Setting parameters is directly tied to certain optimization problems.	[98]
Artificial bee colony optimization (ABC)	Solves optimization problems with constraints. Ability to find the best solutions on a global scale.	Exclusively deals with problems of a small to medium size.	[99]
Whale optimization algorithm (WOA)	Solving complex optimization problems. Simple structure, less required operator. Has optimal performance and efficiency.	Converging slowly. Stagnating at local minima and poor stability.	[106]

typically seeks to determine the best and most appropriate solution to a problem. Because Optimization appears in every problem, its focus has significantly grown in recent decades [91]. It is used in different fields, including computer science, engineering, finance, data analysis, machine learning, bioinformatics, image segmentation problems, fuzzy control systems, and other areas [92]. Various optimization techniques have been developed, where different solutions are evaluated to select the optimal one for the current issue. The efficiency of the best solution is determined by the algorithm employed to deal with the problem. The appropriate algorithm must be chosen to solve the current issue. The optimization process may be initiated by a single or a set of random solutions using an optimization technique. First, the optimization process begins with an initial random solution, which is subsequently iteratively improved. Second, optimization processes generate and enhance solutions [93].

Optimization techniques have been commonly used for image segmentation since many imaging problems may be formulated as minimization ones, with the recovered image as the target minimizer. Meta-heuristic techniques are now considerably more popular with multilevel image thresholding. These methods have garnered much interest because conventional multilevel image thresholding approaches are typically computationally costly. The most widespread meta-heuristic algorithms used to solve the thresholding problem include the particle swarm optimization (PSO) algorithm [94], cuckoo search (CS) algorithm [95], ant colony optimization algorithm (ACO) [96], gray wolf optimization (GWO) algorithm [97], firefly optimization algorithm [98], Artificial bee colony optimization [99], whale optimization algorithm (WOA) [100], Harris hawks optimization (HHO) [101], and equilibrium optimizer (EO) [102]. In addition to these traditional techniques, several recently approved meta-heuristic techniques include the chimp optimization algorithm (ChOA) [103], manta ray foraging optimization [104], slime mould algorithm [105], black widow optimization [106], marine predators' algorithms (MPA) [107], artificial gorilla troops optimizer (GTO) [108] and the golden jackal optimization (GJO) [109].

Table 7 compares various optimization techniques for image segmentation. The table lists the advantages and

TABLE 8. Optimization methods used for skin lesions segmentation.

Author	Year	Methods	Dataset name	No. of tested images
Eltayef K. et al. [140]	2017	Combining Particle Swarm Optimization with Markov Random Field	PH2	200
Aljanabi M. et al. [141]	2018	Artificial bee colony optimization (ABC)	PH2, ISBI 2016, ISBI 2017, DermIs	3,400
Dey N. et al. [142]	2018	Social group optimization (SGO)	Dermis, Dermquest, ISBI2016	140
Sayed G.I. et al. [143]	2020	Multi-swarm coyote optimization algorithm (MCOA)	PH2	44
Masoud Abdulhamid I.A. et al. [144]	2020	New Auxiliary Function with properties in Nonsmooth Global Optimization	PH2, ISBI2016, ISBI2017	3,100
Dash M. et al. [145]	2020	Eight different suitable combinations of conventional clustering (i.e., K-means and Fuzzy C-means (FCMs)) with four swarm intelligence (SI) techniques (i.e., seeker optimization (SO), artificial bee colony (ABC), ant colony optimization (ACO) and particle swarm optimization (PSO))	From 74 patients collected at Psoriasis Clinic and Research Centre, Psoriatreat, Pune, Maharashtra, India.	780
Hawas A.R. et al. [146]	2020	Optimized clustering estimation for neutrosophic graph cut algorithm (OCE-NGC).	ISIC 2016	1,279
Garg S., Jindal B. [147]	2021	K-mean with optimized firefly algorithm (FFA)	ISIC, PH2	1,200
Houssein E.H. et al. [148]	2022	Improved golden jackal optimization algorithm (GJO)	ISIC	Over 12,500

disadvantages of several optimization techniques. Every technique has strengths and weaknesses, as shown in the table below. So, the choice of Optimization is determined by the user's application level. Table 8 discusses the various Optimization methods used by the related researchers to segment skin lesion images.

C. OPTIMIZED DEEP LEARNING

There are various methods for optimizing the learning step of neural networks, and there are few studies about deep neural networks and their applications. Recently, novel optimization ideas also entered the scene in combination with deep learning techniques to improve the reconstruction of images by optimally choosing different parameters/functions of interest in the models. This section shows an overview of the optimized deep-learning techniques. Table 9 discusses the various Optimized Deep-learning methods related studies use to segment skin lesion images.

V. POPULAR EVALUATION METRICS

Several metrics assess the segmentation results for measuring image segmentation algorithms' output quality. The following metrics are frequently used to evaluate the performance: Precision (P), Sensitivity (SEN), Specificity (SPE), Accuracy (ACC), Jaccard index (JAC or IoU), and Dice coefficient (DIC).

A. PRECISION

Precision provides information on the percentage of input data cases assessed as true [159]. Precision is determined according to equation (1).

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

B. SENSITIVITY

Sensitivity is the proportion of positive outcomes (prediction) among those who are positive, as shown in equation (2).

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

C. SPECIFICITY

Specificity is the proportion of negative outcomes (prediction) among those who are negative according to equation (3).

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

TABLE 9. Optimized deep learning methods used for skin lesions segmentation.

Author	Year	Methods	Dataset name	No. of tested images
Yuan Y. et al.[149]	2017	Deep, fully convolutional networks with Jaccard distance	ISIC2016, PH2	1479
S. Vesal. et al. [150]	2018	A convolutional neural network (CNN) called SkinNet (Training network using the Adam optimizer)	ISIC2017	2000
Tan T.Y. et al. [151]	2019	Ensemble deep networks and hybrid clustering models are subsequently constructed depending on the optimized CNN and hybrid clustering.	PH2, ISIC 2017, Dermofit, ALL-IDB2	4,430
Zhang L. et al. [152]	2020	The whale optimization algorithm optimizes the CNN models' weight and biases.	DermIS, Dermquest	22,000
Adegun A.A. et al. [153]	2020	A novel FCN-based DenseNet framework.	HAM10000	Over 10,000
Tan T.Y. et al. [154]	2020	Hybrid learning Practical Swarm Optimization (HLPSO)	Dermofit, PH2, ISIC 2017	1,034
Khan M.A. et al. [155]	2021	Deep learning feature and improved moth flame optimization (IMFO)	ISIC2016, ISIC 2017, ISIC 2018, PH2	6,723
Şahin N. et al. [156]	2021	Robust Optimization of SegNet hyperparameters.	ISBI 2016, ISBI 2017	2,899
Singh L. et al. [157]	2021	Simple linear iterative clustering (SLIC) and ant colony optimization (ACO) algorithms. (SLICACO)	PH2	200
Anupama C.S. et al. [78]	2022	Backtracking Search Optimization Algorithm (BSA) with Entropy-Based Thresholding (EBT), for example, the BSA-EBT technique Shallow Convolutional Neural Network (SCNN)	ISIC	318
Salih O, Duffy KJ [158]	2023	optimized Convolutional Neural Network (CNN) using a genetic algorithm	HAM10000, ISIC2017, ISIC 2018, ISIC 2019	47,346

D. ACCURACY

Accuracy measures the proportion of true results (both true positives and true negatives) among the total number of cases examined, as given in equation (4)

$$Accuracy = \frac{Correct\ Predicitions}{Total\ Predicitions} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

E. JACCARD INDEX

Known as Intersection over union (IoU), also recognized as the Jaccard similarity index, is a measure of similarity for the two sets of data and can be described in the equation (5) [160]:

$$Jaccard\ Index = \frac{2 * TP}{2 * TP + FP + FN} \tag{5}$$

TABLE 10. The number of research papers per year.

Year	Deep Learning	Optimization	Optimized deep learning
2017	11	3	1
2018	34	9	1
2019	65	9	2
2020	59	20	5
2021	103	11	9
2022	139	7	17
Total	**411**	**59**	**35**

F. DICE COEFFICIENT

The dice coefficient (DIC) measures the similarity and overlap between the ground truth and the predicted output. It is described in equation (6):

$$DIC = \frac{2 * TP}{FP + 2 * TP + FN} \tag{6}$$

TABLE 11. Analysis based on accuracy.

ACCURACY %	DermIS	Dermofit	PH2	ISIC 2016	ISIC 2017	ISIC 2018	ISIC 2019	DermQuest
98.00- 100			[146], [155]		[147], [78]			[121]
95.00- 97.99	[141], [142]		[80], [83] [128], [131] [135]- [137] [141], [157]	[80], [139], [141],[144], [146],[149] [155], [156]	[55][57],[80] [128], [131], [136], [137], [139], [141], [144], [155], [158]	[88][136] [158]		
91.00-94.99		[124]	[69],[126], [33], [140], [144]	[31], [142]	[87],[125], [126], [129], [33], [133], [150],[156]	[69],[76] [137],[155]	[128] [158]	[142]
81.00- 90.99			[68]		[132]	[132]		
71.00- 80.99				[132]	[66]			

The TP, TN, FP, and FN denote the true positive, true negative, false positive, and false negative, respectively. It is important to note that high Specificity and Sensitivity indicate the great result of a given method.

VI. ANALYSIS AND DISCUSSION

This section of the paper analyzes skin lesion segmentation methods based on the publication year and quality parameter, i.e., accuracy and datasets utilized.

A. ANALYSIS BASED ON PUBLICATION YEAR

This subsection presents the analysis based on the publication years of the works related to skin lesion segmentation. Table 10 presents the approximate number of papers published in the last six years from the Web of Science Core-Collection (Elsevier, Springer Nature, Hindawi Publishing Group, IEEE, MDPI, et al.). The approximate number of publications published between 2017 and 2022 has been determined. As a result, we found a gradual increase in the interest of researchers in this field with each passing year. Fig. 9, 10, and 11 show the number of research papers published in deep learning, Optimization, and optimized deep learning for skin lesion segmentation, respectively. From Fig. 10, we notice that in 2020, most optimization research papers were published, and the number began to decrease.

On the contrary, in Fig.9 and 11, the number of research papers increases yearly.

B. ANALYSIS BASED ON ACCURACY

In this subsection, we will discuss the accuracy we have achieved according to our papers presented in Table 11. According to each column, we have listed the accuracy achieved by papers on that specific dataset and their corresponding percentage accuracy. Even though we found papers with multiple submissions with different accuracy levels, we have continued to include them. The outcomes of our research involve five papers, i.e., [78], [121], [146], [147], [155], which have achieved accuracy between 98–100% for PH2, ISIC2017 Dermquest datasets. Two papers, i.e., [132] [66], have a low level of accuracy for ISIC 2016 and 2017 data sets, respectively.

C. ANALYSIS BASED ON DATASETS

In this subsection, we present the analysis based on the datasets we have adapted in this research, and various datasets play an important role in melanoma segmentation, feature detection, etc. In Fig. 12, the most common datasets for melanoma detection are displayed. Our research shows that PH2 is now the most widely used dataset, followed by the ISIC 2017 datasets.

VII. CONCLUSION AND FUTURE DIRECTIONS

Melanoma, a dangerous type of disease, is causing increased deaths yearly. In recent years, melanoma has become one of the most common reasons for human death. In the case of early detection, patients will have a better chance of surviving. So, the accuracy of computerized melanoma detection becomes more and more important. Detection of melanoma begins with skin image pre-processing, followed by segmentation. The skin lesion classification may be erroneous if the lesion segmentation is not carried out appropriately.

The chance of detecting melanoma is decreased if the segmentation is performed poorly. Therefore, this paper presents an analytical survey of the major pigmented skin lesion segmentation techniques. The literature survey analysis shows that researchers developed and applied various techniques. These techniques cover pre-processing and segmentation techniques of skin lesion images. Deep learning, Optimization-based, and Optimized Deep learning methods were examined.

The literature survey analysis clearly shows that the researchers developed and applied various computational approaches. However, among them, the rising of deep learning-based and optimized deep learning image segmentation techniques is noticeable since several public datasets have ground truth images. Deep learning-based and optimized techniques are frequently employed for lesion segmentation, producing highly promising segmented outcomes. The important advantage of using the optimization techniques is that it reduces the time complexity and helps increase efficiency without degrading the quality of the image. Nature-inspired optimization algorithms have been used for multilevel thresholding or clustering skin lesion segmentation and are effective and achieve high results compared to traditional algorithms. It is also noticed that traditional techniques (edge-, region-, thresholding-based) approaches are also used but not significantly in this domain.

Deep learning has common issues, including network structure design, 3D data image segmentation model, and loss function design. Designing 3D convolution models to analyze 3D skin lesion image data is a researchable direction. Loss function design has long been a challenge in deep learning research. Optimized Deep Learning models solve these problems.

In addition to segmentation techniques, this research looked at the dataset(s) that the authors utilized in their publication and when training their models. Based on the accuracy achieved by their segmentation technique, we also did a comparison analysis of the utilized research publications. It has also been noticed that the high usage of the PH2 dataset. In addition to PH2, the ISIC 2016 and 2017 datasets have been utilized significantly. However, ISIC 2019 and 2020 datasets should be widely used in the future.

The following are some significant future directions:

- Enhancing image quality with advanced techniques can also improve performance, in addition to the development of CNN models. It will also be possible to segment lesions using an embedding system automatically.
- Different combinations of layers and classifiers can be explored to improve the accuracy of the image segmentation model. An efficient solution is still required to improve the image segmentation model's performance. So, the various new deep learning model designs can be explored by future researchers.
- Mobile dermoscopic image analysis: With various inexpensive dermoscopic designed for smartphones, mobile dermoscopic image analysis is of great interest worldwide, especially in regions with limited access to dermatologists. Typical DL-based image segmentation algorithms have millions of weights. In addition, classical CNN architectures are known to show difficulty in dealing with certain image errors, such as noise and blur. Furthermore, it has been shown that DL-based skin lesion diagnostic models are vulnerable to similar artifacts: different kinds of noise and blur, brightness and contrast changes, dark corners, bubbles, rulers, ink markings, etc. Therefore, the current dermoscopic image segmentation algorithms may not be ideal for execution on typically resource-constrained mobile and edge devices needed for patient privacy so that uploading skin images to remote servers is avoided.

REFERENCES

[1] Dermoscopy Atlas. *The International Atlas of Dermoscopy and Dermatoscopy*. Accessed: Apr. 7, 2023. [Online]. Available: http://www.dermoscopyatlas.com

[2] K. Korotkov and R. Garcia, "Computerized analysis of pigmented skin lesions: A review," *Artif. Intell. Med.*, vol. 56, no. 2, pp. 69–90, Oct. 2012.

[3] Skin Cancer Foundation. *Skin Cancer 101*. Accessed: Apr. 7, 2023. [Online]. Available: https://www.skincancer.org/skin-cancer-information/

[4] American Cancer Society. *Melanoma Skin Cancer*. Accessed: Apr. 7, 2023. [Online]. Available: https://www.cancer.org/cancer/melanoma-skin-cancer.html

[5] M. E. Celebi, N. Codella, and A. Halpern, "Dermoscopy image analysis: Overview and future directions," *IEEE J. Biomed. Health Informat.*, vol. 23, no. 2, pp. 474–478, Mar. 2019.

[6] M. E. Celebi, H. A. Kingravi, B. Uddin, H. Iyatomi, Y. A. Aslandogan, W. V. Stoecker, and R. H. Moss, "A methodological approach to the classification of dermoscopy images," *Computerized Med. Imag. Graph.*, vol. 31, no. 6, pp. 362–373, Sep. 2007.

[7] H. Iyatomi, H. Oka, M. E. Celebi, M. Hashimoto, M. Hagiwara, M. Tanaka, and K. Ogawa, "An improved internet-based melanoma screening system with dermatologist-like tumor area extraction algorithm," *Computerized Med. Imag. Graph.*, vol. 32, no. 7, pp. 566–579, Oct. 2008.

[8] L. Smith and S. MacNeil, "State of the art in non-invasive imaging of cutaneous melanoma," *Skin Res. Technol.*, vol. 17, no. 3, pp. 257–269, Aug. 2011.

[9] S. Q. Wang, H. Rabinovitz, A. W. Kopf, and M. Oliviero, "Current technologies for the in vivo diagnosis of cutaneous melanomas," *Clinics Dermatology*, vol. 22, no. 3, pp. 217–222, May 2004.

[10] A. Wong, J. Scharcanski, and P. Fieguth, "Automatic skin lesion segmentation via iterative stochastic region merging," *IEEE Trans. Inf. Technol. Biomed.*, vol. 15, no. 6, pp. 929–936, Nov. 2011.

[11] P. G. Cavalcanti and J. Scharcanski, "Macroscopic pigmented skin lesion segmentation and its influence on lesion classification and diagnosis," in *Color Medical Image Analysis* (Lecture Notes in Computational Vision and Biomechanics), vol. 6, M. Celebi and G. Schaefer, Eds. Dordrecht, The Netherlands: Springer, 2013, pp. 15–39, doi: 10.1007/978-94-007-5389-1_2.

[12] M. Silveira, J. C. Nascimento, J. S. Marques, A. R. S. Marcal, T. Mendonca, S. Yamauchi, J. Maeda, and J. Rozeira, "Comparison of segmentation methods for melanoma diagnosis in dermoscopy images," *IEEE J. Sel. Topics Signal Process.*, vol. 3, no. 1, pp. 35–45, Feb. 2009.

[13] M. Emre Celebi, Q. Wen, S. Hwang, H. Iyatomi, and G. Schaefer, "Lesion border detection in dermoscopy images using ensembles of thresholding methods," *Skin Res. Technol.*, vol. 19, no. 1, pp. e252–e258, Feb. 2013.

[14] R. Garnavi, M. Aldeen, and J. Bailey, "Computer-aided diagnosis of melanoma using border- and wavelet-based texture analysis," *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no. 6, pp. 1239–1252, Nov. 2012.

[15] K.-A. Norton, H. Iyatomi, M. E. Celebi, S. Ishizaki, M. Sawada, R. Suzaki, K. Kobayashi, M. Tanaka, and K. Ogawa, "Three-phase general border detection method for dermoscopy images using non-uniform illumination correction," *Skin Res. Technol.*, vol. 18, no. 3, pp. 290–300, Aug. 2012.

[16] I. Giotis, N. Molders, S. Land, M. Biehl, M. F. Jonkman, and N. Petkov, "MED-NODE: A computer-assisted melanoma diagnosis system using non-dermoscopic images," *Exp. Syst. Appl.*, vol. 42, no. 19, pp. 6578–6585, Nov. 2015.

[17] DermIS. *Dermatology Information System*. Accessed: Apr. 7, 2023. [Online]. Available: https://www.dermis.net/dermisroot/en/home/index.htm

[18] (2019). *DermQuest*. Accessed: Apr. 7, 2023. [Online]. Available: http://www.dermquest.com

[19] T. Mendonça, P. M. Ferreira, J. S. Marques, A. R. S. Marcal, and J. Rozeira, "PH2–A dermoscopic image database for research and benchmarking," in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2013, pp. 5437–5440.

[20] N. C. F. Codella, D. Gutman, M. E. Celebi, B. Helba, M. A. Marchetti, S. W. Dusza, A. Kalloo, K. Liopyris, N. Mishra, H. Kittler, and A. Halpern, ''Skin lesion analysis toward melanoma detection: A challenge at the international symposium on biomedical imaging (ISBI) 2016, hosted by the international skin imaging collaboration (ISIC),'' in *Proc. IEEE 15th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2018, pp. 168–172.

[21] N. C. F. Codella, D. Gutman, M. E. Celebi, B. Helba, M. A. Marchetti, S. W. Dusza, A. Kalloo, K. Liopyris, N. Mishra, H. Kittler, and A. Halpern, ''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 *Proc. IEEE 15th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2018, pp. 168–172.

[22] N. Codella, V. Rotemberg, P. Tschandl, M. E. Celebi, S. Dusza, D. Gutman, B. Helba, and A. Kalloo, ''Skin lesion analysis toward melanoma detection 2018: A challenge hosted by the international skin imaging collaboration (ISIC),'' 2019, *arXiv:1902.03368*.

[23] P. Tschandl, C. Rosendahl, and H. Kittler, ''The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions,'' *Sci. Data*, vol. 5, no. 1, pp. 1–9, Aug. 2018.

[24] M. Combalia, N. C. F. Codella, V. Rotemberg, B. Helba, V. Vilaplana, and O. Reiter, ''BCN20000: Dermoscopic lesions in the wild,'' 2019, *arXiv:1908.02288*.

[25] V. Rotemberg, ''A patient-centric dataset of images and metadata for identifying melanomas using clinical context,'' *Sci. Data*, vol. 8, no. 1, p. 34, Jan. 2021.

[26] L. Ballerini, R. B. Fisher, B. Aldridge, and J. Rees, ''A color and texture based hierarchical K-NN approach to the classification of non-melanoma skin lesions,'' in *Color Medical Image Analysis* (Lecture Notes in Computational Vision and Biomechanics), vol. 6, M. Celebi and G. Schaefer, Eds. Dordrecht, The Netherlands: Springer, 2013, pp. 63–86, doi: 10.1007/978-94-007-5389-1_4.

[27] P. A. Lio and P. Nghiem, ''Interactive atlas of dermoscopy,'' *J. Amer. Acad. Dermatology*, vol. 50, no. 5, pp. 807–808, May 2004.

[28] W. Li, A. N. Joseph Raj, T. Tjahjadi, and Z. Zhuang, ''Digital hair removal by deep learning for skin lesion segmentation,'' *Pattern Recognit.*, vol. 117, Sep. 2021, Art. no. 107994.

[29] M. E. Celebi, H. A. Kingravi, H. Iyatomi, Y. Alp Aslandogan, W. V. Stoecker, R. H. Moss, J. M. Malters, J. M. Grichnik, A. A. Marghoob, H. S. Rabinovitz, and S. W. Menzies, ''Border detection in dermoscopy images using statistical region merging,'' *Skin Res. Technol.*, vol. 14, no. 3, pp. 347–353, Aug. 2008.

[30] M. R. Guarracino and L. Maddalena, ''SDI+: A novel algorithm for segmenting dermoscopic images,'' *IEEE J. Biomed. Health Informat.*, vol. 23, no. 2, pp. 481–488, Mar. 2019.

[31] N. Nida, A. Irtaza, A. Javed, M. H. Yousaf, and M. T. Mahmood, ''Melanoma lesion detection and segmentation using deep region based convolutional neural network and fuzzy C-means clustering,'' *Int. J. Med. Informat.*, vol. 124, pp. 37–48, Apr. 2019.

[32] A. Pennisi, D. D. Bloisi, D. Nardi, A. R. Giampetruzzi, C. Mondino, and A. Facchiano, ''Skin lesion image segmentation using Delaunay triangulation for melanoma detection,'' *Computerized Med. Imag. Graph.*, vol. 52, pp. 89–103, Sep. 2016.

[33] H. M. Ünver and E. Ayan, ''Skin lesion segmentation in dermoscopic images with combination of YOLO and GrabCut algorithm,'' *Diagnostics*, vol. 9, no. 3, p. 72, Jul. 2019.

[34] E. Vocaturo, E. Zumpano, and P. Veltri, ''Image pre-processing in computer vision systems for melanoma detection,'' in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Dec. 2018, pp. 2117–2124.

[35] S. Majumder and M. A. Ullah, ''Feature extraction from dermoscopy images for melanoma diagnosis,'' *Social Netw. Appl. Sci.*, vol. 1, no. 7, p. 753, Jul. 2019.

[36] R. Garnavi, M. Aldeen, M. E. Celebi, G. Varigos, and S. Finch, ''Border detection in dermoscopy images using hybrid thresholding on optimized color channels,'' *Computerized Med. Imag. Graph.*, vol. 35, no. 2, pp. 105–115, Mar. 2011.

[37] M. Jahanifar, N. Z. Tajeddin, B. M. Asl, and A. Gooya, ''Supervised saliency map driven segmentation of lesions in dermoscopic images,'' *IEEE J. Biomed. Health Inform.*, vol. 23, no. 2, pp. 509–518, May 2018.

[38] J. Premaladha and K. S. Ravichandran, ''Novel approaches for diagnosing melanoma skin lesions through supervised and deep learning algorithms,'' *J. Med. Syst.*, vol. 40, no. 4, p. 96, Apr. 2016.

[39] A. N. Hoshyar, A. A. Jumaily, and A. N. Hoshyar, ''Pre-processing of automatic skin cancer detection system: Comparative study,'' *Int. J. Smart Sens. Intell. Syst.*, vol. 7, no. 3, pp. 1364–1377, Sep. 2014.

[40] S. M. Jaisakthi, A. Chandrabose, and P. Mirunalini, ''Automatic skin lesion segmentation using semi-supervised learning technique,'' 2017, *arXiv:1703.04301*.

[41] D. A. Okuboyejo, O. O. Olugbara, and S. A. Odunaike, ''CLAHE inspired segmentation of dermoscopic images using mixture of methods,'' in *Transactions on Engineering Technologies*. Dordrecht, The Netherlands: Springer, 2014, pp. 355–365.

[42] M. R. Ibraheem and M. Elmogy, ''A non-invasive automatic skin cancer detection system for characterizing malignant melanoma from seborrheic keratosis,'' in *Proc. 2nd Int. Conf. Comput. Inf. Sci. (ICCIS)*, Oct. 2020, pp. 1–5.

[43] A. Agarwal, A. Issac, M. K. Dutta, K. Riha, and V. Uher, ''Automated skin lesion segmentation using K-means clustering from digital dermoscopic images,'' in *Proc. 40th Int. Conf. Telecommun. Signal Process. (TSP)*, Jul. 2017, pp. 743–748.

[44] O. O. Olugbara, T. B. Taiwo, and D. Heukelman, ''Segmentation of melanoma skin lesion using perceptual color difference saliency with morphological analysis,'' *Math. Probl. Eng.*, vol. 2018, pp. 1–9, Feb. 2018.

[45] R. Javid, M. S. M. Rahim, T. Saba, and M. Rashid, ''Region-based active contour JSEG fusion technique for skin lesion segmentation from dermoscopic images,'' *Biomed. Res.*, vol. 30, no. 6, pp. 1–10, 2019.

[46] D. Okuboyejo and O. O. Olugbara, ''Segmentation of melanocytic lesion images using gamma correction with clustering of keypoint descriptors,'' *Diagnostics*, vol. 11, no. 8, p. 1366, Jul. 2021.

[47] M. A. Khan, T. Akram, M. Sharif, T. Saba, K. Javed, I. U. Lali, U. J. Tanik, and A. Rehman, ''Construction of saliency map and hybrid set of features for efficient segmentation and classification of skin lesion,'' *Microsc. Res. Technique*, vol. 82, no. 6, pp. 741–763, Jun. 2019.

[48] A. S. Rajput, V. K. Tanwar, and B. Raman, ''Score-based secure biomedical model for effective skin lesion segmentation over eHealth cloud,'' *ACM Trans. Multimedia Comput., Commun., Appl.*, vol. 17, no. 2s, pp. 1–19, Jun. 2021.

[49] S. Abdelouahed, Y. Filali, and A. Aarab, ''An improved segmentation approach for skin lesion classification,'' *Statist., Optim. Inf. Comput.*, vol. 7, no. 2, p. 533, May 2019.

[50] E. Ahn, J. Kim, L. Bi, A. Kumar, C. Li, M. Fulham, and D. D. Feng, ''Saliency-based lesion segmentation via background detection in dermoscopic images,'' *IEEE J. Biomed. Health Informat.*, vol. 21, no. 6, pp. 1685–1693, Nov. 2017.

[51] M. Z. Alom, M. Hasan, C. Yakopcic, T. M. Taha, and V. K. Asari, ''Recurrent residual convolutional neural network based on U-net (R2U-net) for medical image segmentation,'' 2018, *arXiv:1802.06955*.

[52] D. A. Okuboyejo and O. O. Olugbara, ''A review of prevalent methods for automatic skin lesion diagnosis,'' *Open Dermatology J.*, vol. 12, no. 1, pp. 14–53, Apr. 2018.

[53] M. E. Celebi, Q. Wen, H. Iyatomi, K. Shimizu, H. Zhou, and G. Schaefer, ''A state-of-the-art survey on lesion border detection in dermoscopy images,'' *Dermoscopy Image Anal.*, vol. 10, pp. 97–129, Sep. 2015.

[54] A. A. Adeyinka and S. Viriri, ''Skin lesion images segmentation: A survey of the state-of-the-art,'' in *Proc. Mining Intell. Knowl. Explor., 6th Int. Conf. (MIKE)*, Cluj-Napoca, Romania, Dec. 2018, pp. 321–330.

[55] Y. Guo, A. Ashour, and F. Smarandache, ''A novel skin lesion detection approach using neutrosophic clustering and adaptive region growing in dermoscopy images,'' *Symmetry*, vol. 10, no. 4, p. 119, Apr. 2018.

[56] R. B. Oliveira, M. E. Filho, Z. Ma, J. P. Papa, A. S. Pereira, and J. M. R. S. Tavares, ''Computational methods for the image segmentation of pigmented skin lesions: A review,'' *Comput. Methods Programs Biomed.*, vol. 131, pp. 127–141, Jul. 2016.

[57] F. K. Nezhadian and S. Rashidi, ''Melanoma skin cancer detection using color and new texture features,'' in *Proc. Artif. Intell. Signal Process. Conf. (AISP)*, Oct. 2017, pp. 1–5.

[58] N. Razmjooy, M. Ashourian, M. Karimifard, V. V. Estrela, H. J. Loschi, and D. D. Nascimento, ''Computer-aided diagnosis of skin cancer: A review,'' *Current Med. Imag.*, vol. 16, no. 7, pp. 93–781, Aug. 2020.

[59] P. K. Sahoo, S. Soltani, and A. K. C. Wong, ''A survey of thresholding techniques,'' *Comput. Vis., Graph., Image Process.*, vol. 41, no. 2, pp. 233–260, Feb. 1988.

[60] I. Maglogiannis, E. Zafiropoulos, and C. Kyranoudis, ''Intelligent segmentation and classification of pigmented skin lesions in dermatological images,'' in *Proc. Adv. Artif. Intell., 4th Hellenic Conf.*, Heraklion, Crete, Greece, May 2006, pp. 214–223.

[61] M. Zafar, M. I. Sharif, M. I. Sharif, S. Kadry, S. A. C. Bukhari, and H. T. Rauf, "Skin lesion analysis and cancer detection based on machine/deep learning techniques: A comprehensive survey," *Life*, vol. 13, no. 1, p. 146, Jan. 2023.
[62] M. A. Khan, T. Akram, M. Sharif, A. Shahzad, K. Aurangzeb, M. Alhussein, S. I. Haider, and A. Altamrah, "An implementation of normal distribution based segmentation and entropy controlled features selection for skin lesion detection and classification," *BMC Cancer*, vol. 18, no. 1, p. 638, Dec. 2018.
[63] M. A. Gaheen, E. Ibrahim, and A. A. Ewees, "Edge detection-based segmentation for detecting skin lesions," in *Machine Learning, Big Data, and IoT for Medical Informatics*. Amsterdam, The Netherlands: Elsevier, Jan. 2021, pp. 127–142.
[64] N. Hameed, A. Ruskin, K. Abu Hassan, and M. A. Hossain, "A comprehensive survey on image-based computer aided diagnosis systems for skin cancer," in *Proc. 10th Int. Conf. Softw., Knowl., Inf. Manage. Appl. (SKIMA)*, Dec. 2016, pp. 205–214.
[65] N. Shrivastava and J. Bharti, "Automatic seeded region growing image segmentation for medical image segmentation: A brief review," *Int. J. Image Graph.*, vol. 20, no. 3, Jul. 2020, Art. no. 2050018.
[66] V. R. Balaji, S. T. Suganthi, R. Rajadevi, V. Krishna Kumar, B. Saravana Balaji, and S. Pandiyan, "Skin disease detection and segmentation using dynamic graph cut algorithm and classification through naive Bayes classifier," *Measurement*, vol. 163, Oct. 2020, Art. no. 107922.
[67] M. K. Hasan, L. Dahal, P. N. Samarakoon, F. I. Tushar, and R. Martí, "DSNet: Automatic dermoscopic skin lesion segmentation," *Comput. Biol. Med.*, vol. 120, May 2020, Art. no. 103738.
[68] J. Ramya, H. C. Vijaylakshmi, and H. Mirza Saifuddin, "Segmentation of skin lesion images using discrete wavelet transform," *Biomed. Signal Process. Control*, vol. 69, Aug. 2021, Art. no. 102839.
[69] O. Salih and S. Viriri, "Skin lesion segmentation using stochastic region-merging and pixel-based Markov random field," *Symmetry*, vol. 12, no. 8, p. 1224, Jul. 2020.
[70] O. Salih, S. Viriri, and A. Adegun, "Skin lesion segmentation based on region-edgeMarkov randomfield," in *Advances in Visual Computing* (Lecture Notes in Computer Science), vol. 11845, G. Bebis et al. Cham, Switzerland: Springer, Oct. 2019, pp. 407–418, doi: 10.1007/978-3-030-33723-0_33.
[71] P. K. Goyal, Nirvikar, and M. K. Jain, "Computer-aided diagnosis of melanoma skin cancer: A review," in *Proc. Adv. Data Inf. Sci. (ICDIS)*, vol. 1, 2018, pp. 63–73.
[72] P. A. Pitoy and I. P. G. H. Suputra, "Dermoscopy image segmentation in melanoma skin cancer using Otsu thresholding method," *JELIKU Jurnal Elektronik Ilmu Komputer Udayana*, vol. 9, no. 3, p. 397, Feb. 2021.
[73] D. N. H. Thanh, N. N. Hien, V. B. S. Prasath, U. Erkan, and A. Khamparia, "Adaptive thresholding skin lesion segmentation with Gabor filters and principal component analysis," in *Intelligent Computing in Engineering* (Advances in Intelligent Systems and Computing), vol. 1125, V. Solanki, M. Hoang, Z. Lu, and P. Pattnaik, Eds. Singapore: Springer, 2020, pp. 811–820, doi: 10.1007/978-981-15-2780-7_87.
[74] M. Kavitha., A. S. Arumugam, and T. P. Hong, "Fuzzy clustering technique for segmentation on skin cancer dermoscopic images," in *Fuzzy Mathematical Analysis and Advances in Computational Mathematics* (Studies in Fuzziness and Soft Computing), vol. 419, S. R. Kannan, M. Last, T. P. Hong, and C. H. Chen, Eds. Singapore: Springer, Apr. 2020, pp. 81–89, doi: 10.1007/978-981-19-0471-4_6.
[75] O. Reiter, V. Rotemberg, K. Kose, and A. C. Halpern, "Artificial intelligence in skin cancer," *Current Dermatology Rep.*, vol. 8, pp. 133–140, Sep. 2019.
[76] Y. Gulzar and S. A. Khan, "Skin lesion segmentation based on vision transformers and convolutional neural networks—A comparative study," *Appl. Sci.*, vol. 12, no. 12, p. 5990, Jun. 2022.
[77] M. K. Hasan, M. T. E. Elahi, M. A. Alam, M. T. Jawad, and R. Martí, "DermoExpert: Skin lesion classification using a hybrid convolutional neural network through segmentation, transfer learning, and augmentation," *Informat. Med. Unlocked*, vol. 28, 2022, Art. no. 100819.
[78] C. S. S. Anupama, L. Natrayan, E. L. Lydia, A. R. W. Sait, M. Gamarra, and R. F. Mansour, "Deep learning with backtracking search optimization based skin lesion diagnosis model," *Comput., Mater. Continua*, vol. 70, no. 1, pp. 1297–1313, 2022.
[79] Q. Lin, X. Chen, C. Chen, and J. M. Garibaldi, "Artificial intelligence-based image classification methods for diagnosis of skin cancer: Challenges and opportunities," *Comput. Biol. Med.*, vol. 127, Dec. 2020, Art. no. 104065.
[80] M. Nawaz, Z. Mehmood, T. Nazir, R. A. Naqvi, A. Rehman, M. Iqbal, and T. Saba, "Skin cancer detection from dermoscopic images using deep learning and fuzzy K-means clustering," *Microsc. Res. Technique*, vol. 85, no. 1, pp. 339–351, Jan. 2022.
[81] J. Zhang, C. Petitjean, and S. Ainouz, "Kappa loss for skin lesion segmentation in fully convolutional network," in *Proc. IEEE 17th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2020, pp. 2001–2004.
[82] S. Fawzy, H. E. Moustafa, M. M. Ata, and E. H. AbdelHay, "High performed skin lesion segmentation based on modified active contour," in *Proc. Int. Telecommun. Conf. (ITC-Egypt)*, Jul. 2022, pp. 1–5.
[83] F. F. X. Vasconcelos, A. G. Medeiros, S. A. Peixoto, and P. P. R. Filho, "Automatic skin lesions segmentation based on a new morphological approach via geodesic active contour," *Cognit. Syst. Res.*, vol. 55, pp. 44–59, Jun. 2019.
[84] A. S. Ashour, R. M. Nagieb, H. A. El-Khobby, M. M. A. Elnaby, and N. Dey, "Genetic algorithm-based initial contour optimization for skin lesion border detection," *Multimedia Tools Appl.*, vol. 80, no. 2, pp. 2583–2597, Jan. 2021.
[85] N. E. S. P. do Lago, D. A. Costa, D. G. Pereira, and L. F. A. Campos, "Chan-vese method of targeting applied in localization of melanoma and non-melanoma cancer lesions," *Res. Biomed. Eng.*, vol. 37, no. 3, pp. 583–594, Sep. 2021.
[86] Y. Qiu, J. Xu, "Delving into universal lesion segmentation: Method, dataset, and benchmark," in *Computer Vision—ECCV* (Lecture Notes in Computer Science), vol. 13668, S. Avidan, G. Brostow, M. Cissé, G. M. Farinella, and T. Hassner, Eds. Cham, Switzerland: Springer, Nov. 2022, pp. 485–503, doi: 10.1007/978-3-031-20074-8_28.
[87] N. Moradi and N. Mahdavi-Amiri, "Multi-class segmentation of skin lesions via joint dictionary learning," *Biomed. Signal Process. Control*, vol. 68, Jul. 2021, Art. no. 102787.
[88] M. Taghizadeh and K. Mohammadi, "The fast and accurate approach to detection and segmentation of melanoma skin cancer using fine-tuned YOLOV3 and SegNet based on deep transfer learning," 2022, *arXiv:2210.05167*.
[89] F. Dalila, A. Zohra, K. Reda, and C. Hocine, "Segmentation and classification of melanoma and benign skin lesions," *Optik*, vol. 140, pp. 749–761, Jul. 2017.
[90] M. A. Al-masni, M. A. Al-antari, M.-T. Choi, S.-M. Han, and T.-S. Kim, "Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks," *Comput. Methods Programs Biomed.*, vol. 162, pp. 221–231, Aug. 2018.
[91] V. Sharma, V. K. Jain, and A. Kumar, *An Introduction to Optimization Techniques*. Boca Raton, FL, USA: Chapman & Hall/CRC, Apr. 2021.
[92] M. Sarfraz and S. A. Karim, *Computational Optimization Techniques and Applications*. Norderstedt, Germany: BoD-Books on Demand, Aug. 2021.
[93] Q. Xu, L. Wang, N. Wang, X. Hei, and L. Zhao, "A review of opposition-based learning from 2005 to 2012," *Eng. Appl. Artif. Intell.*, vol. 29, pp. 1–12, Mar. 2014.
[94] B. Akay, "A study on particle swarm optimization and artificial bee colony algorithms for multilevel thresholding," *Appl. Soft Comput.*, vol. 13, no. 6, pp. 3066–3091, Jun. 2013.
[95] S. Pare, A. Kumar, V. Bajaj, and G. K. Singh, "A multilevel color image segmentation technique based on cuckoo search algorithm and energy curve," *Appl. Soft Comput.*, vol. 47, pp. 76–102, Oct. 2016.
[96] A. Qi, D. Zhao, F. Yu, A. A. Heidari, Z. Wu, Z. Cai, F. Alenezi, R. F. Mansour, H. Chen, and M. Chen, "Directional mutation and crossover boosted ant colony optimization with application to COVID-19 X-ray image segmentation," *Comput. Biol. Med.*, vol. 148, Sep. 2022, Art. no. 105810.
[97] A. K. M. Khairuzzaman and S. Chaudhury, "Multilevel thresholding using grey wolf optimizer for image segmentation," *Exp. Syst. Appl.*, vol. 86, pp. 64–76, Nov. 2017.
[98] A. Sharma and S. Sehgal, "Image segmentation using firefly algorithm," in *Proc. Int. Conf. Inf. Technol. (InCITe) Next Gener. IT Summit Theme Internet Things, Connect Worlds*, Oct. 2016, pp. 99–102.
[99] Ş. Öztürk, R. Ahmad, and N. Akhtar, "Variants of artificial bee colony algorithm and its applications in medical image processing," *Appl. Soft Comput.*, vol. 97, Dec. 2020, Art. no. 106799.
[100] S. Mirjalili and A. Lewis, "The whale optimization algorithm," *Adv. Eng. Softw.*, vol. 95, pp. 51–67, Feb. 2016.
[101] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, "Harris hawks optimization: Algorithm and applications," *Future Gener. Comput. Syst.*, vol. 97, pp. 849–872, Aug. 2019.
[102] A. Faramarzi, M. Heidarinejad, B. Stephens, and S. Mirjalili, "Equilibrium optimizer: A novel optimization algorithm," *Knowl.-Based Syst.*, vol. 191, Mar. 2020, Art. no. 105190.

[103] M. Khishe and M. R. Mosavi, "Chimp optimization algorithm," *Exp. Syst. Appl.*, vol. 149, Jul. 2020, Art. no. 113338.

[104] W. Zhao, Z. Zhang, and L. Wang, "Manta ray foraging optimization: An effective bio-inspired optimizer for engineering applications," *Eng. Appl. Artif. Intell.*, vol. 87, Jan. 2020, Art. no. 103300.

[105] S. Li, H. Chen, M. Wang, A. A. Heidari, and S. Mirjalili, "Slime mould algorithm: A new method for stochastic optimization," *Future Gener. Comput. Syst.*, vol. 111, pp. 300–323, Oct. 2020.

[106] V. Hayyolalam and A. A. Pourhaji Kazem, "Black widow optimization algorithm: A novel meta-heuristic approach for solving engineering optimization problems," *Eng. Appl. Artif. Intell.*, vol. 87, Jan. 2020, Art. no. 103249.

[107] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H. Gandomi, "Marine predators algorithm: A nature-inspired metaheuristic," *Exp. Syst. Appl.*, vol. 152, Aug. 2020, Art. no. 113377.

[108] B. Abdollahzadeh, F. S. Gharehchopogh, and S. Mirjalili, "Artificial gorilla troops optimizer: A new nature-inspired metaheuristic algorithm for global optimization problems," *Int. J. Intell. Syst.*, vol. 36, no. 10, pp. 5887–5958, Oct. 2021.

[109] N. Chopra and M. Mohsin Ansari, "Golden jackal optimization: A novel nature-inspired optimizer for engineering applications," *Exp. Syst. Appl.*, vol. 198, Jul. 2022, Art. no. 116924.

[110] S. Dargan, M. Kumar, M. R. Ayyagari, and G. Kumar, "A survey of deep learning and its applications: A new paradigm to machine learning," *Arch. Comput. Methods Eng.*, vol. 27, no. 4, pp. 1071–1092, Sep. 2020.

[111] Y. Guo, Y. Liu, T. Georgiou, and M. S. Lew, "A review of semantic segmentation using deep neural networks," *Int. J. Multimedia Inf. Retr.*, vol. 7, no. 2, pp. 87–93, 2018.

[112] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Medical Image Computing and Computer-Assisted Intervention—MICCAI* (Lecture Notes in Computer Science), vol. 9351, N. Navab, J. Hornegger, W. Wells, and A. Frangi, Eds. Cham, Switzerland: Springer, Oct. 2015, pp. 234–241, doi: 10.1007/978-3-319-24574-4_28.

[113] Z. Zhou, X. Quan, and Y. Niu, "IDUNet++: An improved convolutional neural network for melanoma skin lesion segmentation based on UNet++," in *Proc. 2nd Int. Conf. Electron. Inf. Eng., Big Data, Comput. Technol. (EIBDCT)*, vol. 12642, May 2023, pp. 562–567.

[114] F. Milletari, N. Navab, and S.-A. Ahmadi, "V-net: Fully convolutional neural networks for volumetric medical image segmentation," in *Proc. IEEE 3D Vis.*, Oct. 2016, pp. 565–571.

[115] F. Bagheri, M. J. Tarokh, and M. Ziaratban, "Skin lesion segmentation based on mask RCNN, multi atrous full-CNN, and a geodesic method," *Int. J. Imag. Syst. Technol.*, vol. 31, no. 3, pp. 1609–1624, Sep. 2021.

[116] R. Girshick, "Fast #," in *Proc. IEEE Int. Conf. Comput. Vis.*, 2015, pp. 1440–1448.

[117] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 6, pp. 1137–1149, Jun. 2017.

[118] K. He, G. Gkioxari, P. Dollar, and R. Girshick, "Mask R-CCN," in *Proc. IEEE Int. Conf. Comput. Vis.*, Oct. 2017, pp. 2961–2969.

[119] L.-C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam, "Encoder–decoder with atrous separable convolution for semantic image segmentation," in *Proc. Eur. Conf. Comput. Vis. (ECCV)*, 2018, pp. 801–818.

[120] L.-C. Chen, G. Papandreou, F. Schroff, and H. Adam, "Rethinking atrous convolution for semantic image segmentation," 2017, *arXiv:1706.05587*.

[121] H. Harkat, J. M. P. Nascimento, and A. Bernardino, "Fire segmentation using a DeepLabv3+ architecture," *Proc. SPIE*, vol. 11533, pp. 134–145, Sep. 2020.

[122] B. S. Lin, K. Michael, S. Kalra, and H. R. Tizhoosh, "Skin lesion segmentation: U-Nets versus clustering," in *Proc. IEEE Symp. Ser. Comput. Intell. (SSCI)*, Nov. 2017, pp. 1–7.

[123] B. Bozorgtabar, S. Sedai, P. K. Roy, and R. Garnavi, "Skin lesion segmentation using deep convolution networks guided by local unsupervised learning," *IBM J. Res. Develop.*, vol. 61, nos. 4–5, p. 6, Jul. 2017.

[124] S. Izadi, Z. Mirikharaji, J. Kawahara, and G. Hamarneh, "Generative adversarial networks to segment skin lesions," in *Proc. IEEE 15th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2018, pp. 881–884.

[125] Z. Mirikharaji and G. Hamarneh, "Star shape prior in fully convolutional networks for skin lesion segmentation," in *Proc. Med. Image Comput. Comput. Assist. Intervent. (MICCAI)*, Sep. 2018, pp. 737–745.

[126] M. Goyal, A. Oakley, P. Bansal, D. Dancey, and M. H. Yap, "Skin lesion segmentation in dermoscopic images with ensemble deep learning methods," *IEEE Access*, vol. 8, pp. 4171–4181, 2020.

[127] F. Xie, J. Yang, J. Liu, Z. Jiang, Y. Zheng, and Y. Wang, "Skin lesion segmentation using high-resolution convolutional neural network," *Comput. Methods Programs Biomed.*, vol. 186, Apr. 2020, Art. no. 105241.

[128] S. Banerjee, S. K. Singh, A. Chakraborty, A. Das, and R. Bag, "Melanoma diagnosis using deep learning and fuzzy logic," *Diagnostics*, vol. 10, no. 8, p. 577, Aug. 2020.

[129] R. Kaymak, C. Kaymak, and A. Ucar, "Skin lesion segmentation using fully convolutional networks: A comparative experimental study," *Exp. Syst. Appl.*, vol. 161, Dec. 2020, Art. no. 113742.

[130] K. Zafar, S. O. Gilani, A. Waris, A. Ahmed, M. Jamil, M. N. Khan, and A. Sohail Kashif, "Skin lesion segmentation from dermoscopic images using convolutional neural network," *Sensors*, vol. 20, no. 6, p. 1601, Mar. 2020.

[131] S. Öztürk and U. Özkaya, "Skin lesion segmentation with improved convolutional neural network," *J. Digital Imag.*, vol. 33, pp. 970–985, Aug. 2020.

[132] M. A. Al-masni, D.-H. Kim, and T.-S. Kim, "Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification," *Comput. Methods Programs Biomed.*, vol. 190, Jul. 2020, Art. no. 105351.

[133] L. Liu, Y. Y. Tsui, and M. Mandal, "Skin lesion segmentation using deep learning with auxiliary task," *J. Imag.*, vol. 7, no. 4, p. 67, Apr. 2021.

[134] Z. Mirikharaji, K. Abhishek, S. Izadi, and G. Hamarneh, "D-LEMA: Deep learning ensembles from multiple annotations–application to skin lesion segmentation," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jun. 2021, pp. 1837–1846.

[135] V. Anand, S. Gupta, D. Koundal, S. R. Nayak, P. Barsocchi, and A. K. Bhoi, "Modified U-NET architecture for segmentation of skin lesion," *Sensors*, vol. 22, no. 3, p. 867, Jan. 2022.

[136] C. Akyel and N. Arıcı, "LinkNet-b7: Noise removal and lesion segmentation in images of skin cancer," *Mathematics*, vol. 10, no. 5, p. 736, Feb. 2022.

[137] M. D. Alahmadi, "Multiscale attention U-Net for skin lesion segmentation," *IEEE Access*, vol. 10, pp. 59145–59154, 2022.

[138] C. Zhao, R. Shuai, L. Ma, W. Liu, and M. Wu, "Segmentation of skin lesions image based on U-Net $++$," *Multimedia Tools Appl.*, vol. 81, no. 6, pp. 8691–8717, Mar. 2022.

[139] Q. Ma, K. Mao, G. Wang, L. Xu, and Y. Zhao, "LCAUnet: A skin lesion segmentation network with enhanced edge and body fusion," 2023, *arXiv:2305.00837*.

[140] K. Eltayef, Y. Li, and X. Liu, "Lesion segmentation in dermoscopy images using particle swarm optimization and Markov random field," in *Proc. IEEE 30th Int. Symp. Comput.-Based Med. Syst. (CBMS)*, Jun. 2017, pp. 739–744.

[141] M. Aljanabi, Y. Özok, J. Rahebi, and A. Abdullah, "Skin lesion segmentation method for dermoscopy images using artificial bee colony algorithm," *Symmetry*, vol. 10, no. 8, p. 347, Aug. 2018.

[142] N. Dey, V. Rajinikanth, A. Ashour, and J. M. Tavares, "Social group optimization supported segmentation and evaluation of skin melanoma images," *Symmetry*, vol. 10, no. 2, p. 51, Feb. 2018.

[143] G. I. Sayed, G. Khoriba, and M. H. Haggag, "The novel multi-swarm coyote optimization algorithm for automatic skin lesion segmentation," *Evol. Intell.*, pp. 1–33, Aug. 2020, doi: 10.1007/s12065-020-00450-4.

[144] I. A. Masoud Abdulhamid, A. Sahiner, and J. Rahebi, "New auxiliary function with properties in nonsmooth global optimization for melanoma skin cancer segmentation," *BioMed Res. Int.*, vol. 2020, pp. 1–14, Apr. 2020.

[145] M. Dash, N. D. Londhe, S. Ghosh, V. K. Shrivastava, and R. S. Sonawane, "Swarm intelligence based clustering technique for automated lesion detection and diagnosis of psoriasis," *Comput. Biol. Chem.*, vol. 86, Jun. 2020, Art. no. 107247.

[146] A. R. Hawas, Y. Guo, C. Du, K. Polat, and A. S. Ashour, "OCE-NGC: A neutrosophic graph cut algorithm using optimized clustering estimation algorithm for dermoscopic skin lesion segmentation," *Appl. Soft Comput.*, vol. 86, Jan. 2020, Art. no. 105931.

[147] S. Garg and B. Jindal, "Skin lesion segmentation using K-mean and optimized fire fly algorithm," *Multimedia Tools Appl.*, vol. 80, no. 5, pp. 7397–7410, Feb. 2021.

[148] E. H. Houssein, D. A. Abdelkareem, M. M. Emam, M. A. Hameed, and M. Younan, "An efficient image segmentation method for skin cancer imaging using improved golden jackal optimization algorithm," *Comput. Biol. Med.*, vol. 149, Oct. 2022, Art. no. 106075.

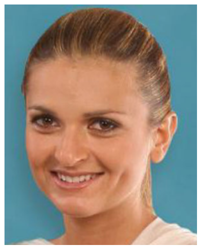
[149] Y. Yuan, M. Chao, and Y.-C. Lo, "Automatic skin lesion segmentation using deep fully convolutional networks with Jaccard distance," *IEEE Trans. Med. Imag.*, vol. 36, no. 9, pp. 1876–1886, Sep. 2017.

[150] S. Vesal, N. Ravikumar, and A. Maier, "SkinNet: A deep learning framework for skin lesion segmentation," in *Proc. IEEE Nucl. Sci. Symp. Med. Imag. Conf. Proc. (NSS/MIC)*, Nov. 2018, pp. 1–3.
[151] T. Y. Tan, L. Zhang, C. P. Lim, B. Fielding, Y. Yu, and E. Anderson, "Evolving ensemble models for image segmentation using enhanced particle swarm optimization," *IEEE Access*, vol. 7, pp. 34004–34019, 2019.
[152] L. Zhang, H. J. Gao, J. Zhang, and B. Badami, "Optimization of the convolutional neural networks for automatic detection of skin cancer," *Open Med.*, vol. 15, no. 1, pp. 27–37, Jan. 2020.
[153] A. A. Adegun and S. Viriri, "FCN-based DenseNet framework for automated detection and classification of skin lesions in dermoscopy images," *IEEE Access*, vol. 8, pp. 150377–150396, 2020.
[154] T. Y. Tan, L. Zhang, and C. P. Lim, "Adaptive melanoma diagnosis using evolving clustering, ensemble and deep neural networks," *Knowl.-Based Syst.*, vol. 187, Jan. 2020, Art. no. 104807.
[155] M. A. Khan, M. Sharif, T. Akram, R. Damaševičius, and R. Maskeliūnas, "Skin lesion segmentation and multiclass classification using deep learning features and improved moth flame optimization," *Diagnostics*, vol. 11, no. 5, p. 811, Apr. 2021.
[156] N. Şahin, N. Alpaslan, and D. Hanbay, "Robust optimization of SegNet hyperparameters for skin lesion segmentation," *Multimedia Tools Appl.*, vol. 81, no. 25, pp. 36031–36051, Oct. 2022.
[157] L. Singh, R. R. Janghel, and S. P. Sahu, "SLICACO: An automated novel hybrid approach for dermatoscopic melanocytic skin lesion segmentation," *Int. J. Imag. Syst. Technol.*, vol. 31, no. 4, pp. 1817–1833, Dec. 2021.
[158] O. Salih and K. J. Duffy, "Optimization convolutional neural network for automatic skin lesion diagnosis using a genetic algorithm," *Appl. Sci.*, vol. 13, no. 5, p. 3248, Mar. 2023.
[159] M. Vakili, M. Ghamsari, and M. Rezaei, "Performance analysis and comparison of machine and deep learning algorithms for IoT data classification," 2020, *arXiv:2001.09636*.
[160] J. Bertels, "Optimizing the dice score and Jaccard index for medical image segmentation: Theory and practice," in *Proc. Med. Image Comput. Comput. Assist. Intervent. (MICCAI)*, Oct. 2019, Shenzhen, China, pp. 92–100.

KHALID M. HOSNY (Senior Member, IEEE) was born in Zagazig, Egypt, in 1966. He received the B.Sc., M.Sc., and Ph.D. degrees from Zagazig University, Egypt, in 1988, 1994, and 2000, respectively. From 1997 to 1999, he was a Visiting Scholar with the University of Michigan, Ann Arbor, and the University of Cincinnati, Cincinnati, USA. He is a Professor of information technology with the Faculty of Computers and Informatics, Zagazig University. He is also a Senior Member of ACM. He has published four edited books and more than 140 articles in international journals. His research interests include image processing, pattern recognition, multimedia, and computer vision. He is an editor and a scientific reviewer of more than 50 international journals. He was among the top 2% of scientists according to the Stanford ranking, from 2020 to 2022.

DOAA ELSHOURA received the M.S. degree from Zagazig University, Egypt, in 2016. She is a Teaching Assistant with the Department of Information Technology, Faculty of Computers and Informatics, Zagazig University. Her current research interest includes image processing.

EHAB R. MOHAMED received the M.S. degree in data compression and the Ph.D. degree in routing techniques of computer networks from the Faculty of Engineering, Zagazig University. He is currently an Assistant Professor and the Head of the Information Technology Department with the Faculty of Computer and Informatics, Zagazig University. He is an Official Instructor for EMC 2 in Egypt. He has published about 30 articles in national and international journals. His current research fields are SDN, data compression, image and data processing, and networking. He is a reviewer in different journals as JDCTA.



ELENI VROCHIDOU received the Diploma degree in embedded systems, the M.Sc. degree in automatic control systems, and the Ph.D. degree in signal processing from the Department of Electrical and Computer Engineering, Democritus University of Thrace (DUTH), Greece, in 2004, 2007, and 2016, respectively.

She is currently a part-time Lecturer with the Department of Computer Science (IHU), International Hellenic University, where she is teaching bachelor's courses from 2005 to 2022 and master's courses from 2018 to 2022. As a researcher, she is a member of the Machine Learning and Vision (MLV) Research Group, where she participates in research projects. Her research interests are intelligent systems, signal processing, pattern recognition, and embedded systems. She has several publications in international scientific conferences, journals, and book chapters in her research areas.

GEORGE A. PAPAKOSTAS received the Diploma, M.Sc., and Ph.D. degrees in electrical and computer engineering from the Democritus University of Thrace (DUTH), Greece, in 1999, 2002, and 2007, respectively.

He has 15 years of experience in large-scale systems design as a Senior Software Engineer and a Technical Manager. He is the Head of the Machine Learning and Vision (MLV) Research Group. He is a tenured Full Professor with the Department of Computer Science, International Hellenic University, Greece. He has (co)authored more than 200 publications in indexed journals, international conferences, book chapters, one book (in Greek), two edited books, and six journal special issues. His publications have over 3600 citations with an H-index of 34 (Google Scholar). His research interests include machine learning, computer/machine vision, pattern recognition, and computational intelligence.

Prof. Papakostas is a member of the ACM, IAENG, MIR Laboratories, EUCogIII, and the Technical Chamber of Greece (TEE). He was a reviewer in numerous journals and conferences.