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Review

A Survey on Computer-Aided Intelligent Methods to Identify and Classify Skin Cancer

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Abstract: Melanoma is one of the skin cancer types that is more dangerous to human society. It easily spreads to other parts of the human body. An early diagnosis is necessary for a higher survival rate. Computer-aided diagnosis (CAD) is suitable for providing precise findings before the critical stage. The computer-aided diagnostic process includes preprocessing, segmentation, feature extraction, and classification. This study discusses the advantages and disadvantages of various computer-aided algorithms. It also discusses the current approaches, problems, and various types of datasets for skin images. Information about possible future works is also highlighted in this paper. The inferences derived from this survey will be useful for researchers carrying out research in skin cancer image analysis.

Keywords: skin cancer; melanoma; feature extraction; segmentation; classification; CAD

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1. Introduction

The abnormalities in the skin layers cause various skin diseases [1,2]. Some skin diseases are identified and cured by clinicians. Other skin diseases exist without symptoms and cannot be diagnosed by doctors with the naked eye. One such skin cancer caused by UV radiation affecting the genetic material of skin layers is melanoma [3,4]. The types of skin diseases is shown in Figure 1.

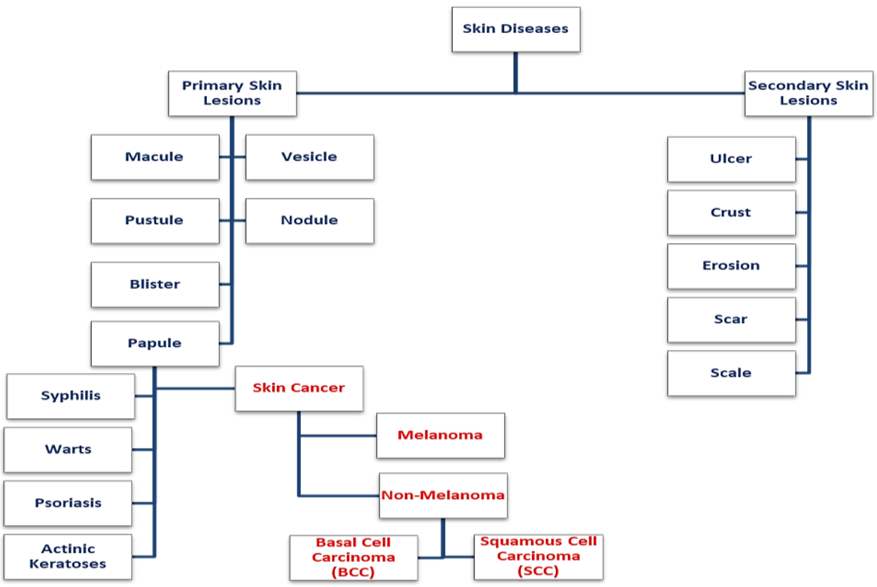

Figure 1. Types of Skin Diseases.

Melanoma is the 17th most common cancer in the world, out of 200 different types [5]. Based on the American Cancer Society, nearly 7650 people will die from melanoma in 2022 (about 5080 men and 2570 women) [6]. Skin cancer rates have been rapidly increasing in recent times. Skin cancer affects human beings of all ages [7]. A skin lesion is a disorder in the skin cells. Skin cancer (carcinoma) can take many different forms [8]. Most types of melanoma begin at the top of the skin's layers. There are types of melanoma that could become intrusive by penetrating through deeper layers of the skin [9]. The non-melanoma types of cancer are diagnosed and cured, but in some rare cases, they can be fatal [10–12]. Any type of skin cancer that develops in the basal, squamous, or Merkel cells of the skin is referred to as nonmelanoma skin cancer. Melanoma is a type of cancer that appears in the melanocytes of the skin. Basal cell carcinoma can be seen anywhere on the skin; however, it typically appears on the head and neck. It primarily results from sun exposure or manifests in patients who have had radiation therapy in their youth. Sun exposure is the primary cause of squamous cell carcinoma, which can be found in various skin types. It can also manifest on skin that has been burned, harmed by chemicals, or exposed to x-rays. Lips with old scars are frequently affected by squamous cell cancer [10,11].

The skin surface is typically covered by radial growth, which describes the behavior of superficially spreading melanoma. It may, however, also begin to penetrate the skin (called vertical growth). It frequently has a flat surface and a border that is irregular. It can have various shades such as red, blue, brown, black, grey, and white. On the skin, a mole may occasionally serve as the origin of a superficially spreading melanoma [13,14]. The various types of melanoma and non-melanoma are given in Table 1.

Table 1. Different Types of melanoma and non-melanoma [10–14].

MELANOMA TYPES		NON-MELANOMA TYPES	
Superficial Spreading Melanoma		Basal Cell Carcinoma	
Nodular Melanoma		Squamous Cell Carcinoma	
Lentigo Maligna Melanoma		Merkel Cell Carcinoma	
Amelanotic Melanoma		Cutaneous T-Cell Lymphona	
Rare Melanoma Types; a. Cutaneous Melanoma b. Metastatic Melanoma c. Mucosal Melanoma d. Ocular Melanoma		Kaposi Sarcoma	

Skin cancer is an abnormality in the human skin. It affects the tissues of the human skin. Skin cancer includes melanoma and non-melanoma types. It is captured by an imaging device. AI techniques work well with images. It gives accurate results and supports the clinicians in making accurate decisions for treatment planning.

In recent research, identifying the different types of melanoma and non-melanoma classification is more challenging [15,16]. Dermoscopy is an instrument that identifies a wide range of skin problems, including malignant and benign tumors. Although dermoscopy improves melanoma diagnosis, it cannot replace histopathologic evaluation [17,18]. The lack of methods for detecting melanoma at an early stage leads the researchers to aim for computer-aided diagnosis methods [19,20]. The availability of advanced image processing methods, artificial intelligence methods, and decision-making mechanisms to construct computer-aided diagnostic systems can provide a comprehensive solution to aid in the early detection of skin cancer melanoma. The advanced intelligent methods are based on deep learning and machine learning algorithms that are used in skin cancer image classification and image segmentation [21,22].

The structure of the paper is as follows: Section 2 focuses on the image data collection. The list of collected data has been tabulated with the websites and the total number of skin images sorted into melanoma skin images and other skin disease images. Section 3 deals with image pre-processing techniques. Section 4 explains the image segmentation methods. Section 5 describes various feature extraction techniques. Section 6 explains the classification methods for melanoma and non-melanoma. Sections 7 and 8 provide the conclusions about the different AI-based diagnostic methods.

2. Skin Cancer Image Database

Images that are already present in numerous datasets have been used in this work. In addition, researchers are also actively carrying out diagnosis for skin treatment with the real-time images. The image dataset has been developed for research and benchmarking objectives to enable comparative studies on image-based methods, machine learning, and deep learning algorithms of dermoscopic images. The quality of the dataset is affected by clinical, dermatoscope, and pathological parameters. The skin diagnosis is validated using clinical and synthetic data that are presently available. The datasets include patients from the United States of America, Portugal, Scotland, Denmark, and Australia. Melanoma is more than 20 times more common in white people than in dark skin populations. The incidence of melanoma is lower among dark skin populations due to the protective effect of melanin, but the risk is higher for non-melanoma types. According to statistics, the average age of people diagnosed with melanoma is 50 and above. These datasets have been used by many researchers to develop AI-based diagnostic tools. A brief description on the datasets is shown in Table 2.

Table 2. Skin Image Dataset.

Reference	Dataset	No of Skin Image	Melanoma Images	Other Skin Disease Images	Web-Link
Gutman, David, et al. (2016) [23]	ISIC-2016	1279	248	1031	https://challenge.isic-archive.com/data (Accessed on 15 November 2022)
Codella N, et al. (2017) [24]	ISIC-2017	2750	521	2229	
Noel Codella. et al. (2018) [25] Rehman M., (2018) [26]	ISIC-2018 (HAM10000, MSK)	10,015	1113	8902	
Rehman M., (2018) [26] Noel C. F. Cordella, et al. (2018) [25] Marc Combalia, et al. (2019) [27]	ISIC-2019 (BCN_20000, HAM10000, MSK)	25,331	4522	20,809	
Rotemberg, V, et al. (2021) [28]	ISIC-2020	33,126	6927	26,199	

Table 2. *Cont.*

Reference	Dataset	No of Skin Image	Melanoma Images	Other Skin Disease Images	Web-Link
Lei Bi, et al. (2017) [29] T. Y. Satheesha, et al. (2017) [30] Omar abuzaghleh, et al. (2015) [31] Catarina Barata (2014) [32]	PH2	200	40	160	https://www.fc.up.pt/addi/ph2%20database.html (Accessed on 15 November 2022)
Argenziano, et al. (2000) [33] Aurora Saez, et al. (2014) [34]	Interactive Atlas of Dermoscopy	1000	270	730	https://dermoscopy.org/atlas/default.asp (Accessed on 15 November 2022)
Pacheco, Andre, et al. (2020) [35]	PAD-UFES-20	2298	52	2246	https://data.mendeley.com/datasets/zr7vgbcyr2/1 (Accessed on 15 November 2022)
Rees, Aldridge, et al. (2013) [36]	Dermofit Image Library	1300	76	1224	https://licensing.edinburgh-innovations.ed.ac.uk/product/dermofit-image-library (Accessed on 15 November 2022)
NewZealand Dermatological Society (2021) [37]	DermNet NZ	>21,000	-	-	https://dermnetnz.org/image-library (Accessed on 15 November 2022)
Jeremy Kawahara, et al. (2018) [38]	7-Point Criteria Evaluation Database	1011	252	759	https://derm.cs.sfu.ca/Download.html (Accessed on 15 November 2022)
Jessica B. Diniz, et al. (2017) [39]	ISDI	571	125	446	NA
Svetlana. S, et al. (2017) [40]	Asan and Hallym Dataset	17,250	599	16,651	https://figshare.com/articles/figure/Asan_and_Hallym_Dataset_Thumbnails_/5406136 (Accessed on 15 November 2022)
I. Giotis, et al. (2015) [41]	MED-NODE Dataset	170	70	100	https://www.cs.rug.nl/~imaging/databases/melanoma_naevi/ (Accessed on 15 November 2022)
Andersen, L. B. [42]	NCI GDC Portal	2883	2333	550	https://portal.gdc.cancer.gov/ (Accessed on 15 November 2022)
Hosny KM, et al. (2019) [43–45]	DIS and DermQuest	206	119	87	http://www.dermis.net http://www.dermquest.com (Accessed on 15 November 2022)

3. Skin Cancer Image Preprocessing

Image pre-processing is used to improve the image quality and enhance the original image. It is a required step in the acquisition of dermoscopy images. It is required because the captured image may lack clarity. Hair color, scars, and skin tone differences will accumulate on the surface of the human skin. As a result, the images should be preprocessed to accurately assess the affected skin lesion [46]. An image can be preprocessed in a variety of ways. Some of the methods are: 1. Image enhancement 2. Image restoration 3. Hair Removal. An illustration of the various pre-processing techniques is given in Figure 2.

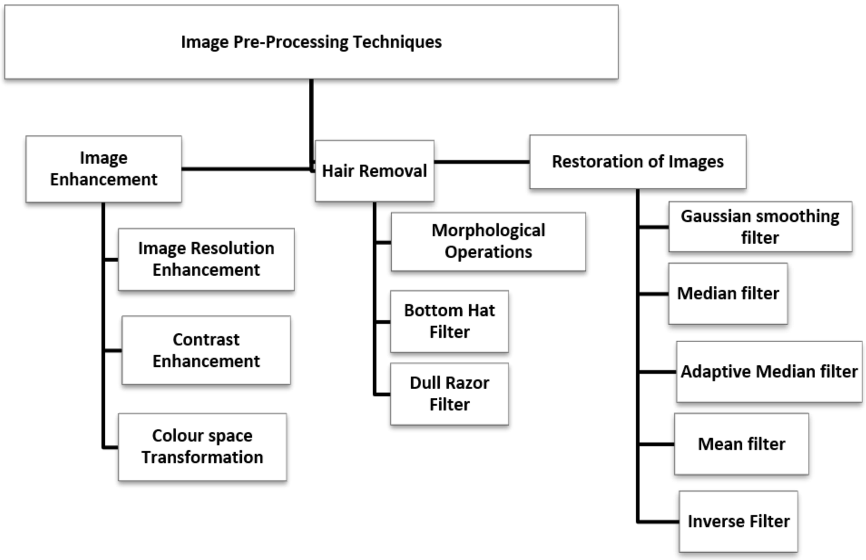

Figure 2. Types of Image Pre-Processing.

3.1. Image Enhancement

Image enhancement is the technique of enhancing digital pictures to make them more appropriate for display [47]. Under low lighting conditions, object detection, and identification can be enhanced using image enhancement techniques. It can be used to change the contrast of an image, making it lighter, darker, or both. The researchers have created several techniques for enhancing image quality [48].

3.1.1. Image Resolution Enhancement

Data augmentation can be used for image resolution enhancement, which includes rotation, shifting, brightness, reflection, and resizing images. Due to the fact that some of the images in the dataset have small pixel dimensions, different image acquisition factors may apply. The luminance and size of the image can thus change significantly. The lesion image dataset is likely to contain a variety of images because each acquisition tool has a different set of criteria. The pixel strength of all images is standardized to ensure that the data are consistent and noise-free [47]. In order to preserve the features and shape of the skin lesion, a lower resolution may be used after resizing the input images to prevent shape distortion of the skin lesions [49].

3.1.2. Color Space Transformation

Increasing the contrast of an image means transferring it to a new space where the image intensity is directly proportional to its main components. To accomplish this, the image color space is initially converted from RGB to LAB. Then, the remaining processes are performed in the sublayer L. Regulating the sublayer L affects the intensity of the pixels while preserving the image's original color [50]. Luminance components are best suited for distinguishing hair and dark pigments. As a result, the LUV color space can be used to transform color spaces [46]. Since the shadow effect in the value channel is more obvious than in other channels and color spaces, the original RGB color space image is converted to the hue, saturation, and value (HSV) space in order to reduce the effect of non-uniform illumination or shadow [51]. Images that contain only shades of gray and no other colors are known as "grayscale" images. A range of monochromatic tones from black to white is referred to as grayscale. Images are converted to grayscale using the luminance value of each pixel, which is also known as the brightness or intensity. It is measured on a scale from black to white. Each pixel in an RGB digital image has three distinct luminance values: red, green, and blue [52].

3.1.3. Contrast Enhancement

The primary function of a histogram equalization-based method is to improve the contrast of an input image. The image histogram will be below if the difference in brightness between the lowest and highest values in the image is small. Histogram equalization is a method for boosting the histogram's value and contrast to make the following stages of image processing easier [53]. An improvised version of Adaptive Histogram Equalization (AHE) that was created specifically to preprocess medical image data is called Contrast Limited Adaptive Histogram Equalization (CLAHE). Each tile in the image is processed using the CLAHE technique, which also enhances each tile's contrast. As a result, the output will be more accurate than simply boosting an image's contrast [54]. The contrast-enhancing technique known as adaptive histogram equalization (AHE) has proven to be effective and is intended to be widely applicable. However, there are two issues with it: its slow speed and the excessively amplified noise. The algorithms presented address these issues. For the method to run more quickly on all-purpose computers, these algorithms include interpolated AHE [55].

3.2. Image Restoration

The goal of image restoration techniques is to recreate the original image from a damaged observation. This deterioration may be caused by a variety of factors, including motion blur, noise, or even an out-of-focus camera [56]. Table 3 provides some of the filtering methods for image restoration.

Table 3. Restoration of images by various filtering methods.

Author	Method	Advantages	Drawback
Ghosh P (2022) [52]	Mean Filter	In addition to reducing noise, it could maintain edges.	Suppress the finer details in an image.
H. Zhang (2021) [53]	Median Filter	With median filtering, noise is eliminated while edges are preserved.	Blurring of image in process.
Pizer (1987) [55]	Adaptive Median Filter	Remove the noise and enhance the image.	The median filter replaces the potential noisy pixels but not regional features, such as the existence of edges.
Martínez, L.T (2021) [56]	Gaussian Smoothing Filter	Images are sharpened and smoothened.	High-frequency image elements are distorted and removed.
Pizer (1987) [55]	Inverse Filter	Image enhancement from blurred images.	Spectral indices with a clearly defined fringe.

3.3. Hair Removal

Hair removal techniques are used to filter the thick hairs and thin blood vessels. The dark hair is removed from the image using the Dull Razor algorithm. To replace the non-hair pixels and smooth the algorithm's output, interpolation is used in the algorithm. However, undesirable blurring and color bleeding frequently result from this procedure [57]. A direction normal to the hair orientation produces a strong derivative response in hair structures. Thus, long, hair-like structures can be removed using oriented derivative filters. The maximum magnitude of these filters is preprocessed to remove hair. A graphical model is then used to reconstruct the skin image [58].

4. Skin Lesion Segmentation

The first step in image analysis and data extraction is image segmentation. Image segmentation has a direct impact on how well people are able to understand the image as a whole. The location of the lesion border must be determined using a segmentation algorithm. Then, the features of the skin lesion must be extracted to determine the lesion's malignant or benign status. The segmentation of the skin lesion must be precise. Algorithms for feature extraction and classification must be properly selected [59]. The early detection and diagnosis of melanoma are improved by the skin lesion image segmentation technique. Some of the segmentation methods used for skin lesions are explained in the subsequent sections.

4.1. Threshold Based Segmentation

With a threshold-based segmentation algorithm, pixels with values below the threshold are ignored because they are thought to be free of skin cancer. Segmentation allows us to determine if any areas are affected by skin cancer [59]. The threshold method used to segment an image turns a grayscale image into a binary image by applying a threshold value. This threshold value is chosen using Otsu's method by maximizing the image's variance. A global threshold is computed by Otsu's method to be used to convert an intensity image to a binary image. Morphological operations are used to remove the lower pixels to suppress light structures connected to the image border and to fill the image region and holes. The steps used in Otsu's algorithm are given below:

1. Select an initial estimate of T (Threshold).
2. Compute the means of the two regions determined by T.
3. Set the new T as the average of the two means.
4. Repeat step 3 until the difference in T in successive iterations is smaller than a predefined parameter.

With adaptive thresholding, each pixel's threshold value is determined by the values of the pixels around it. This adaptive method offers a better conversion from grayscale image to binary image and can assist in overcoming the varying lighting conditions in the input image [60]. The general location and shape of a lesion are determined using initial segmentation and then double thresholding to focus on an area of the image where the ideal lesion boundary is present. The goal of double thresholding is to choose a range of threshold values that contains the optimal threshold value at each boundary point because the optimal threshold value at one boundary point may differ from that at another boundary point. Additionally, double thresholding lessens the quantity of noisy regions produced by the intensity of thresholding [61].

4.2. Edge Based Segmentation

Edge-based segmentation methods commonly refer to the process of segmenting an image based on the edges between regions by searching for edge pixels and connecting them to form image contours. However, two methods are established for applying such methods: manually, by using the mouse to draw lines that represent image boundaries between regions, and automatically, by implementing some edge detection filters. The watershed segmentation algorithm and the Laplacian of gaussian filter are two examples of edge detection filters [62]. A derivative filter called the Laplacian filter is used to locate areas of abrupt intensity change in an image in order to identify edges. A derivative filter called the Laplacian is typically used to reduce the sensitivity to noise in images that have already been smoothed with other filters [63]. Edge-based and region-based segmentation are both used in the watershed segmentation algorithm. Finding the watershed lines in the input image and segmenting the prominent regions is the goal of the watershed segmentation algorithm [62]. A clever edge detector can locate pixels close to the edge, but it struggles to locate precise edges [64]. There are two phases to the segmentation strategy. The nonlinear diffusion model is used in the first method to detect edges by selectively removing low-level contrast information, which is typically related to noises and hairs. By using the Canny edge detector on the previously smoothed image, the second stage determines the lesion edges [65].

4.3. Region Based Segmentation

In region growing segmentation, the region is developed repeatedly by comparing it with all of its unallocated neighboring pixels. The measure of similarity is the difference between the intensity value of a pixel and the mean of the region. The individual region receives the pixel with the lowest degree of dissimilarity as determined along these lines. When the intensity difference between the region means and the new pixel noticeably exceeds a predetermined threshold, this handle stops [66]. The skin lesion images lack clearly defined edges, and the region's shape is highly erratic, making segmentation difficult. For segmenting the objects in the images, the majority of segmentation algorithms use either edge or region information. However, in order to segment the foreground image, the GrabCut segmentation algorithm makes use of both the boundary and region information [67].

4.4. Soft Computing Based Segmentation

The study of soft computing has grown in popularity and significance over time. It is used in many different research fields, but it is mainly used in medical image analysis to provide various soft computing-based segmentation techniques. To determine the validity of implementation based on the model and the datasets, it is essential to evaluate the algorithms. The evaluation of various soft computing techniques takes segmentation and classification into consideration. To gauge the algorithm's effectiveness, a variety of techniques can be used. Among them are accuracy (AC), dice score (D), Jaccard coefficient (J), true detection rate (TDR), sensitivity, and specificity. Table 4 gives different soft computing-based segmentation methods with its performance analysis.

Table 4. Different soft computing-based segmentation methods.

Author	Dataset	Method	Performance Analysis (PA)			
			Accuracy	**Specificity**	**Sensitivity**	**Other PA**
S. Albahli, et al. [68–70]	ISIC 2016	Active Contour	93.9%	95.2%	94.2%	D-1 J-98.9%
M. Goyal, et al. [71]	ISIC 2017	End to End Ensemble Segmentation Method	94.1%	97.9%	89.9%	-
	PH_2		93.8%	92.9%	98.7%	-
R.Ramadan, et al. [72]	ISIC 2017	Color U-Net Semantic Segmentation Deep Model	93.13%	96.21%	83.64%	D-85.63% J-74.88%
	ISIC 2018		94.58%	95.85%	91.57%	D-90.96% J-83.42%
G. Zhang, et al. [73]	ISIC 2017	DSM Network	94.3%	-	85.9%	J-78.5% D-87.5%
	PH_2		93.1%	-	88.9%	J-89.1% D-92%
Y. Xie, et al. [74]	ISIC 2017	MB-DCNN Model	93.8%	87.4%	96.8%	J-80.4%
	PH_2		97.7%	96.7%	94.6%	J-89.4%

Table 4. *Cont.*

Author	Dataset	Method	Performance Analysis (PA)			
			Accuracy	Specificity	Sensitivity	Other PA
P. Chen, et al. [75]	ISIC 2017	Recurrent Attentional Convolutional Network (O-Net)	94.71%	96.3%	89.70%	J-80.36% D-87.04%
	PH_2		95.14%	96.75%	89.23%	J-86.15% D-92.12%
A.Wong, et al. [76]	60 real images	Iterative Stochastic Region Merging Method	-	-	9.16%	TDR-93%
Y. Yuan, et al. [77]	ISBI 2016	CDNN	95.7%	96.5%	92.4%	J-76.5%
P.G.Cavalcanti, et al. [78,79]	Skin Images	Otsu-RGB	85.0%	85.5%	92.2%	-
Y.Yuan, et al. [80]	ISBI 2016	FCN ensemble	95.5%	96.6%	91.8%	-
Bagheri, et al. [81]	Dermquest	Mask R-CNN	99.25%	99.64%	94.92%	J-76.5%
	ISBI 2017	Retina-Deeplab	94.18%	96.51%	88.37%	J-80.04%

5. Feature Extraction

The process of computing parameters that reflect the characters of the input image is known as feature extraction. ABCD features include area, border, color, and diameter [82]. Geometrical features include area, perimeter, thinness ratio, bounding length and width, major axis length, minor axis length, aspect ratio, rectangular aspect ratio, area ratio, maximum radius, minimum radius, radius ratio, standard deviation, mean of all radii, and Haralick ratio. Texture features include First Order Statistics (FOS), Gray Level Co-Occurrence Matrix of Second Order Statistics (GLCM), and Gray Level Run Length Matrix of Higher Order Statistics (GLRLM). Mean, median, mode, and range [83]. Some feature extraction methods and their performance are listed in Table 5.

Table 5. The different types of skin cancer image feature extraction.

Author	Dataset	Feature	Method	Performance Analysis
Jacinth., et al. (2020) [82]	Med-Node	ABCD	Total Dermoscopy Score	Accuracy-88%
Murugan A., et al. (2021) [83]	ISIC	GLCM	Support Vector Machine	Accuracy-89.31%
Annaby M. H., et al. (2021) [84]	ISIC	Color, Geometry, Texture	Support Vector Machine	Accuracy-97.40% Sensitivity-100% Specificity-95.1% AUC-99.91%
Rehman A., et al. (2020) [85]	PH2	ABCD	Total Dermatoscopy Score (TDS)	Accuracy-93.5% Sensitivity-90.3% Specificity-95%
	ISIC			Accuracy-91.45% Sensitivity-92% Specificity-91.5%

6. Skin Lesion Classification

A computer-aided diagnosis system has been developed for the identification of the skin disease [86–88]. Proper detection and classification can lead to earlier detection, reducing subsequent risks to the patient. Skin cancer can be classified as melanoma or non-melanoma depending on the extracted features. Various classification approaches, along with the performance analysis, are listed in Table 6.

Table 6. The different types of skin cancer image classification.

Author	Dataset	Method	Performance Analysis (%)		
			Sensitivity	Specificity	Accuracy
Dorj UO, et al. [89]	PH_2	SVM	96	97	-
		AdaBoost	96	98	-
		Bag of Features (BoF)	93	96	-
	Atlas	SVM	98	99	-
		AdaBoost	47	92	-
		Bag of Features (BoF)	77	96	-
Zhao C, et al. [90]	ISIC 2019	SLA-Style GAN	85.6	96.1	96.4
		DenseNet 201	68.2	95.6	98.84
Zhang J, et al. [91]	ISIC 2017	ARL-CNN 50	65.8	89.6	85
Tang P, et al. [92]	ISIC 2016	GP-CNN-DTEL	32	99.7	86.3
Carcagni, et al. [93]	ISBI 2017	ResNet 50 + RA Pooling + Rank Opt	60.7	88.4	83
Li Y, et al. [94]	ISIC 2017	Lesion Indexing Network(LIN)	50.4	93	85.2

7. Inferences from the Survey

A detailed explanation of image datasets, image pre-processing, lesion segmentation, feature extraction, classification, and performance metrics has been provided. The advantages and disadvantages of the techniques have been determined, and the following conclusion is drawn from the survey:

1. To improve diagnostic accuracy, deep learning algorithms typically require a large amount of diverse, balanced, and high-quality training data that represents each class of skin lesions.
2. The features extracted from the images must be accurate to ensure high classification accuracy.
3. Most of the algorithms are computationally complex and, hence, difficult to use in practical situations.

8. Conclusions and Future Scope

A major factor in the early diagnosis of skin cancer is the development of computer-aided diagnosis to detect melanoma, which is a problem for global health. The process of detecting skin cancer involves several steps, including preprocessing, image segmentation, feature extraction, classification, and performance analysis. The performance can be improved by increasing the number of features and by modifying the existing techniques. Theoretically, there are several AI-based techniques that yield good detection results. However, the practical feasibility of these approaches is still a problem due to the computational complexity of the AI-based methods. Several researchers are currently trying to tackle this problem, which can make these systems practically feasible.

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