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RESEARCH PAPER

# A survey of recent advances in analysis of skin images

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**Abstract**

Skin disorders significantly impact quality of life, necessitating advanced diagnostic tools. Machine Learning (ML) and Deep Learning (DL), particularly Convolutional Neural Networks (CNNs), offer promising solutions. ML aids in image segmentation and lesion classification, while DL captures intricate features for improved accuracy. Challenges include limited annotated data, the 'black box' nature of AI decision-making, and seamless integration into clinical workflows. Recent advancements such as development of ML and DL algorithms and availability of publicly available datasets, hold promise for earlier diagnoses and improved outcomes in dermatology. Building ML and DL models robust to variations in image quality, lighting conditions, and patient demographics is hence, paramount to enhance the accuracy and efficiency of skin image analysis in clinical practice. In conclusion, while ML and DL techniques show promise, exploring hybrid approaches combining the strengths of both could lead to more robust diagnostic tools for dermatology, revolutionizing skin disorder diagnosis and treatment.

**Keywords** Skin analysis · Machine learning · Image processing · Deep learning · Image segmentation · Feature extraction · Image classification

## 1 Introduction

Skin conditions rank as the fourth most prevalent category of human illnesses, impacting nearly a third of the global population Flohr and Hay [31]. In recent years, there has been a growing interest in leveraging advanced technologies for the analysis of skin images to address the challenges associated with traditional diagnostic methods Haenssle et al. [39, 40] Maron et al. [70]. Figure 1 indicates the regional distribution of skin and subcutaneous disease burden measured indisability-adjusted life year (DALY), where one DALY represents the loss of the equivalent of one year of full health. Karimkhani et al. [54]

Skin image analysis plays a crucial role in dermatology due to the increasing prevalence of skin disorders and the importance of early detection and accurate diagnosis. With skin cancer rates on the rise globally Arnold et al. [16], timely identification of malignant lesions is imperative for effective treatment and improved patient out- comes. Additionally, skin diseases such as psoriasis, eczema, acne, ringworm, and other skin disorders, can significantly impact individuals' quality of life Christensen and Jafferany [27], underscoring the need for precise diagnostic tools to tailor treatment plans to each patient's specific condition. Moreover, advancements in technology have made it possible to capture high-resolution images of skin lesions, providing clinicians with detailed visual information for analysis Dinnes et al. [28].

Dermatological imaging techniques, such as dermoscopy and clinical photography Baig et al. [18] offer valuable insights into various skin conditions, ranging from benign lesions to potentially life-threatening malignancies like melanoma. However, the accurate interpretation of these images is often challenging due to the complex nature of skin lesions, the presence of artifacts, and the subjective nature of visual inspection.

Automated skin image analysis tools offer the potential to streamline the diagnostic process, reduce subjectivity, and improve diagnostic accuracy, thereby enhancing patient care. By leveraging machine learning and deep learning algorithms, researchers aim to develop robust systems capable of accurately classifying skin lesions,

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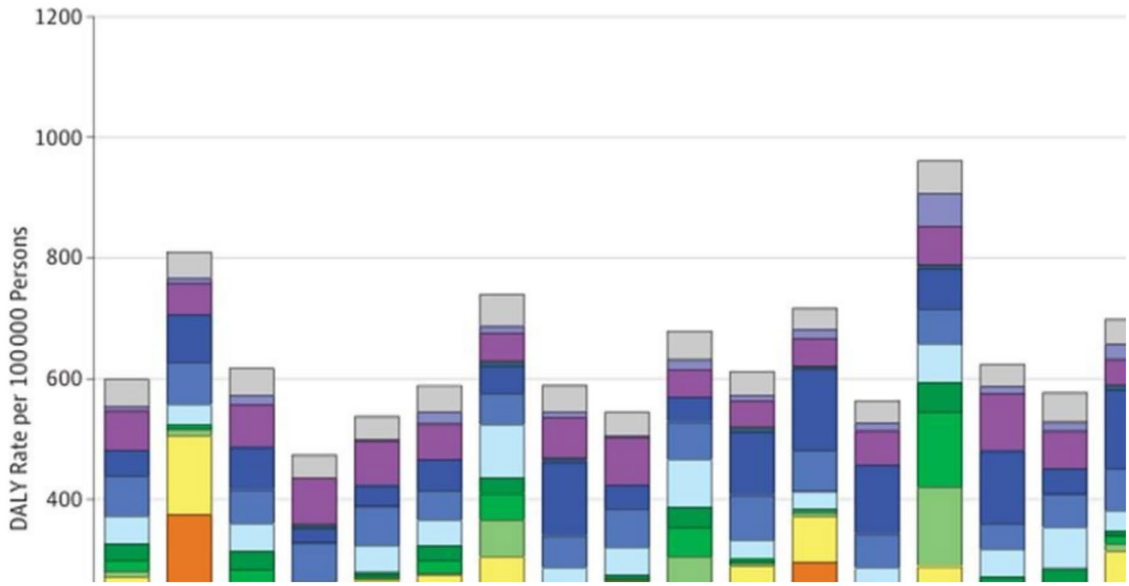


**Fig. 1** Regional distribution of skin and subcutaneous disease burden

facilitating early detection, personalized treatment strategies, and ultimately, better outcomes for patients.

Figure 1 depicts the regional distribution of skin and subcutaneous diseases burden investigated by the Global Burden of disease (GBD) 2013 Study Karimkhani et al. [54].

This paper aims to provide a survey of recent advances in the analysis of skin images. Through this, we have presented the various techniques and methodologies of automated skin image analysis, with a focus on addressing the need for accurate and efficient dermatological diagnosis and management. This survey endeavors to inform researchers, clinicians, and other stakeholders about the latest developments in this rapidly evolving field thus providing a better understanding of the current landscape and identify opportunities for future research.

Automated skin image analysis tools offer the potential to streamline the diagnostic process, reduce subjectivity, and improve diagnostic accuracy, thereby enhancing patient care. By leveraging machine learning and deep learning algorithms, researchers aim to develop robust systems capable of accurately classifying skin lesions, facilitating early detection, personalized treatment strategies, and ultimately, better outcomes for patients.

The remainder of this paper is organized as follows: Sect. 2 describes the Methodology for this survey, Sect. 3 introduces the Image Processing Techniques used in analysis of skin images. Section 4 introduces the Machine Learning and Deep Learning Techniques used for Skin Disease recognition. Section 5 lists the various datasets available for analysis of skin images. Section 6 summarizes the full text and discusses challenges and future research directions in skin image analysis.

## 2 Methodology

To conduct the literature survey, we employed a systematic approach focused on gathering relevant research articles related to skin image analysis, dermatology, and related fields. The primary databases searched were PubMed and Scopus, renowned repositories for scholarly articles in the medical and scientific domains. The search query used a combination of keywords and phrases to ensure comprehensive coverage of the topic. Specifically, the query included terms such as "Skin Image Analysis", "Dermatology", "Skin diseases", "Dermoscopy", and "Dermoscopic" to capture studies related to skin imaging and dermatological conditions. Additionally, the query incorporated terms associated with image processing and machine learning techniques, such as "Image Processing", "Machine Learning", "Deep Learning", "CNN", "Convolutional Neural Networks", "Neural Networks", and "Artificial Intelligence", to identify articles focusing on computational methods for analyzing skin images. By utilizing this query, we aimed to retrieve a diverse range of scholarly works relevant to our research objectives, enabling a comprehensive review of recent advances and developments in skin image analysis methodologies.

To ensure the quality and relevance of the studies included in our literature survey, certain exclusion criteria were applied. Studies were excluded if they were geographically limited, focusing solely on a specific region or population group, thus potentially limiting the generalizability of findings. Additionally, studies deemed methodologically weak, lacking robust experimental design or statistical analysis, were excluded to maintain the integrity of the review. Furthermore, studies deemed irrelevant to the objectives of our research, such as those not addressing skin image analyses or employing unrelated methodologies were also excluded. By implementing these exclusion criteria, we aimed to refine the selection process and include only high-quality, pertinent studies in our review, ensuring the reliability and validity of our findings.

The methodology for this survey has been depicted in the workflow in Fig. 2.

Figure 3 emphasizes on the keywords and prominent words in the literature. The keywords and prominent words revealed through the word cloud generated from the titles of the studies encompass critical themes in the field of skin image analysis. "Melanoma," a significant term in dermatology, underscores the emphasis on detecting and classifying this potentially fatal form of skin cancer. The prominence of terms like "classification" and "detection" highlights the central focus on developing and refining methods for accurately categorizing and identifying skin lesions, including melanoma. These keywords reflect the overarching goal of enhancing diagnostic accuracy and early detection of skin diseases through advanced image analysis techniques.

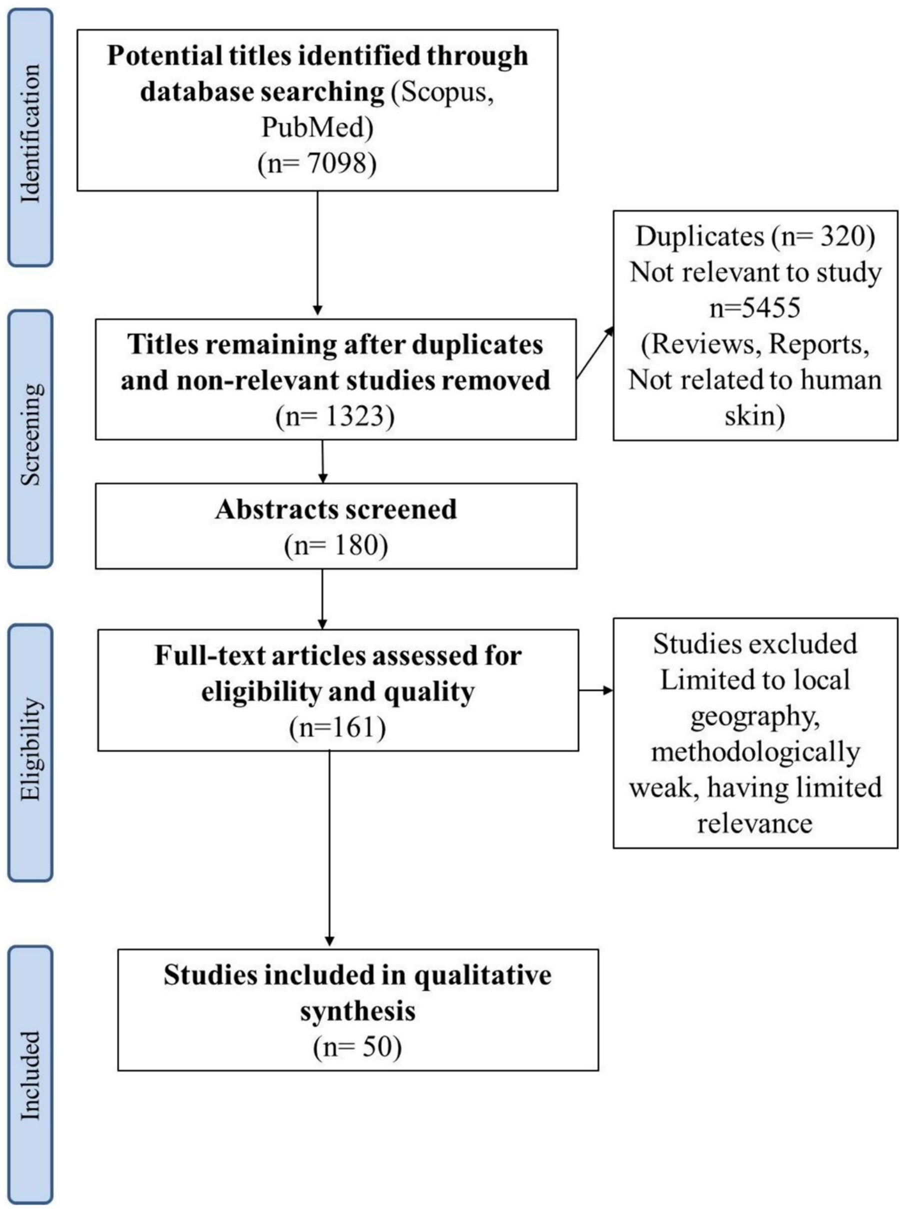


**Fig. 2** Workflow for survey

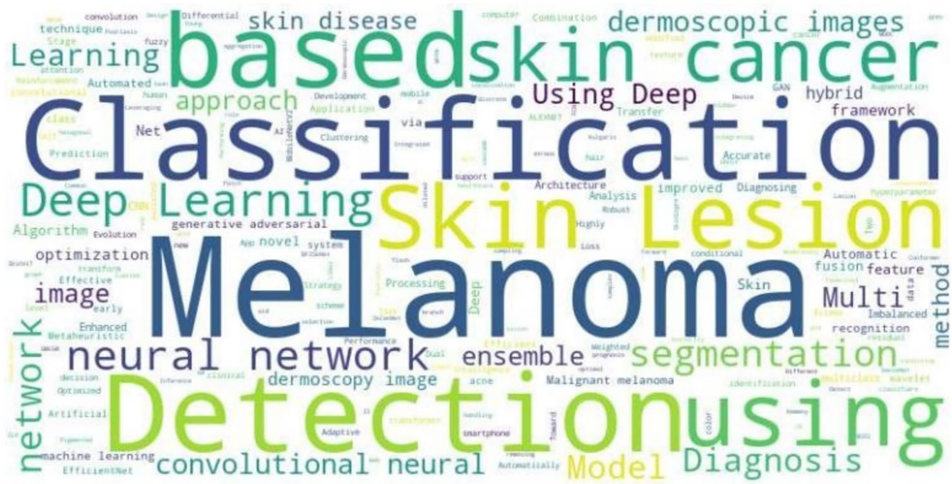


Fig. 3 Word cloud for keywords and prominent words in literature

## 3 Image processing techniques in skin image analysis

Figure 4 depicts the Image Processing pipeline in Skin Image Analysis.

Image processing techniques have played a crucial role in the analysis of skin images for various applications such as skin cancer detection, disease diagnosis, and cosmetic analysis. It involves the use of various techniques to analyze images for better understanding and interpretation by experts. Conventional image processing techniques have been widely used in skin image analysis for a long time. These techniques typically involve a series of preprocessing steps, feature extraction techniques, segmentation techniques, and classification to extract relevant information from the images.

The integration of Machine Learning and Deep Learning techniques with conventional image processing techniques has also led to significant progress in skin image analysis Escalé-Besa et al. [29]. For example, conventional feature extraction techniques such as texture analysis can be

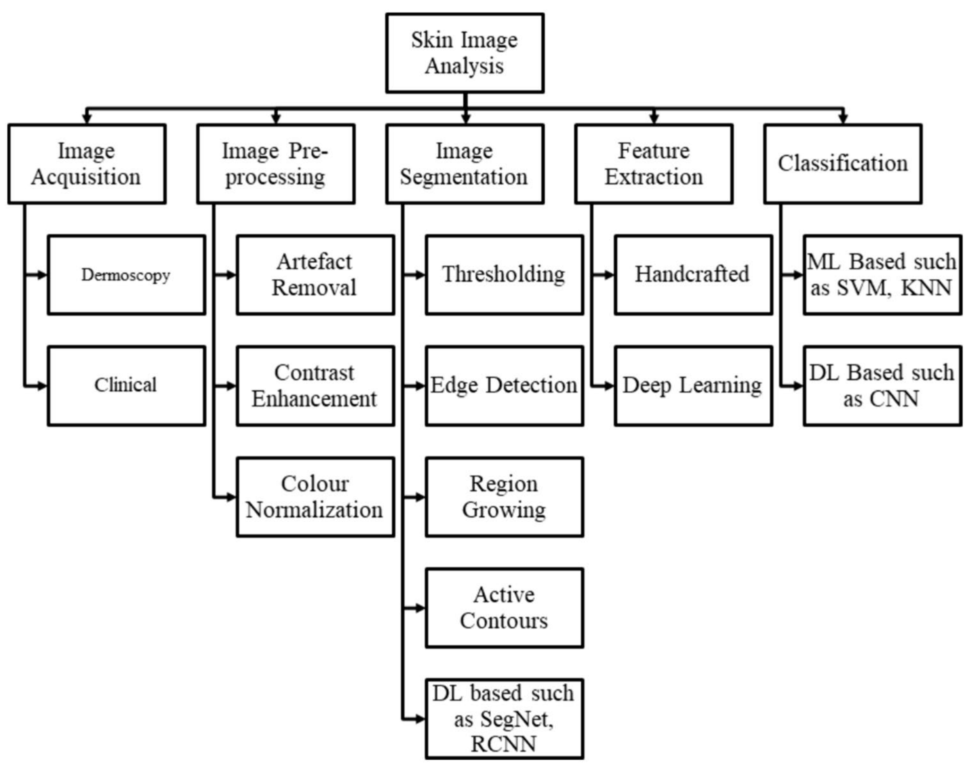


Fig. 4 Image processing techniques in skin image analysis

combined with Deep Learning techniques to improve performance. Researchers have developed hybrid models that use both handcrafted features and automatically learned features to achieve improved performance in skin lesion classification tasks Mahum and Aladhadh [69] Hagerty et al. [41] Sharma et al. [102] Abbas and Celebi [7]. Another example is the use of transfer learning Mahbod et al. [68] Jasil and Ulagamuthalvi [50], where pretrained Deep Learning models are used to extract features from skin images. This can be particularly useful when limited labeled data is available, as the pre-trained models can be fine-tuned for the specific skin analysis task. The integration of Machine Learning and Deep Learning approaches with conventional image processing techniques has also led to the development of more interpretable models, by using techniques such as attention mechanisms Zhang et al. [126] or saliency maps Jahanifar et al. [49] to highlight relevant regions in skin images. This section details the various conventional and machine learning based approaches for skin image analysis.

## 3.1 Image preprocessing

Image preprocessing is an essential step in skin image analysis, which involves enhancing the quality and contrast of the image, reducing noise, and removing unwanted artifacts. The pre-processing step helps to improve the accuracy and reliability of the subsequent analysis steps such as feature extraction, segmentation, and classification. Preprocessing techniques involve various image enhancement and noise reduction methods. Joseph and Olugbara [52] have investigated the effects of preprocessing methods on segmentation results. Common preprocessing techniques used in skin image analysis include color normalization, contrast stretching, and denoising.

### 3.1.1 Color normalization

Color normalization techniques are used to correct for variations in illumination and imaging conditions. Their objective is to establish a uniform color appearance among various images or rectify specific color biases. One common approach involves converting the image into a color space that is less influenced by changes in lighting conditions, like the LAB color space. Schaefer et al. [94] have proposed a preprocessing step to normalize color and enhance contrast of dermoscopic images before applying to segmentation algorithms. Their technique uses Automatic Color Equalization (ACE), a technique that combines two popular methods (Grayworld and MaxRGB) and performs local adjustment based on color spatial distribution. This conversion helps normalize the color channels and enhances the overall consistency of color distribution, making it easier for subsequent analysis. Skin lesions or features of interest might exhibit different degrees of contrast, influencing their visibility and subsequent analysis.

### 3.1.2 Contrast enhancement

Contrast enhancement techniques Saiwaeo et al. [92] are used to adjust the brightness and contrast of the image to highlight important features. Histogram equalization is a common contrast enhancement technique that redistributes the pixel intensity values in the image to improve the contrast. Adaptive histogram equalization (AHE) is a variation of histogram equalization that enhances the contrast locally, which is particularly useful for images with non-uniform lighting conditions.

Contrast stretching techniques strive to improve local contrast by expanding the range of pixel intensities in the image. This can be accomplished through methods like histogram equalization or adaptive histogram equalization (AHE) as proposed by Hanlon et al. [43]. These techniques redistribute the intensity values in the image, enhancing the visibility of crucial details. Skin images obtained in clinical environments or through different imaging modalities may be susceptible to noise, which can impede precise analysis and diagnosis.

### 3.1.3 Artifact removal

In the field of dermatological imaging, precise interpretation of skin lesions holds paramount importance for ensuring effective diagnosis and planning optimal treatment strategies. However, the presence of various artifacts, such as hair and residual marker marks, pose significant challenges by potentially obscuring lesion features and compromising image fidelity.

To address these challenges, researchers and clinicians have devised several artifact removal methodologies. Preprocessing techniques, including filtering algorithms, morphological operations Nida et al. [80], and inpainting techniques, are frequently employed to eliminate unwanted artifacts while preserving pertinent lesion information. Filtering methods such as median or Gaussian filters aid in noise reduction and smoothing out irregularities in the image, thereby enhancing the clarity of lesion boundaries. Morphological operations, such as erosion and dilation, serve to refine segmentation masks and eliminate extraneous elements such as stray hairs or marker residues. Additionally, sophisticated inpainting algorithms are utilized to intelligently reconstruct missing or obscured regions of the image, seamlessly blending them with the surrounding skin texture.

Bansal and Sridhar [20] have proposed a model that employs a novel approach based on hexagonal sampling and generative adversarial networks (GANs) to segment hairs and inpaint hair gaps. Initially, Attention U-net is utilized to segment hairs in pixel units, followed by the proposed HEXA-GAN with ReLU activation function for inpainting. The HEXA-GAN consists of two GANs (G1 and G2), where G1 performs coarse inpainting using hexagonal sampling, and G2 refines the inpainted images with a contextual attention layer.

Kasmi et al. [56] propose SharpRazor, an algorithm designed for automatic removal of hair and ruler marks from dermoscopy images, addressing challenges in segmentation and structured detection. The algorithm utilizes a multi-filter approach to detect hair of varying widths against varying backgrounds, while avoiding false detection of vessels and bubbles. SharpRazor employs grayscale plane modification, hair enhancement, segmentation using tri-directional gradients, and multiple filters for hair detection, along with an alternate entropy-based processing adaptive thresholding method.

Efficient removal of artifacts such as hair strands and marker residues not only enhances the reliability and accuracy of dermatological image analysis but also facilitates more precise lesion segmentation, feature extraction, and classification, thereby culminating in enhanced diagnostic precision and informed treatment decisions. Moreover, by ensuring the integrity of image data, artifact removal techniques contribute to the reproducibility and robustness of automated analysis algorithms, ultimately benefiting patients through more effective management of skin conditions.

De-noising methods are applied to reduce undesirable noise while retaining significant image features. Various denoising algorithms, including Gaussian filtering, median filtering, or wavelet-based denoising methods, can be utilized as proposed by Goceri [35]. The objective of these techniques is to reduce noise while preserving relevant information to the greatest extent possible. By employing these techniques, the image quality can be enhanced, and the impact of image artifacts can be minimized.

#### 3.1.4 Other preprocessing techniques

Edge enhancement techniques are used to improve the sharpness of edges in the image. Common edge enhancement techniques include Sobel, Prewitt, and Roberts operators, which are used to detect edges based on their gradient magnitude and orientation. Laplacian of Gaussian (LoG) and Difference of Gaussian (DoG) filters are also popular for detecting edges and other features in the image. Sengupta et al. [98] present a valuable and noninvasive approach for automatically detecting the edges of skin lesions. Their proposed segmentation method involves utilizing an edge detection operator with an optimized threshold value. Before applying the edge detection technique, the clinical skin lesion image goes through preprocessing steps, including hair removal, contrast enhancement, and filtering techniques, to ensure accurate segmentation. To enhance the accuracy of edge detection, the researchers introduce and fine-tune a parameter called the "fudge factor", which plays a crucial role in adjusting the threshold value. Through optimization of this factor, the algorithm achieves more precise and reliable results in identifying the edges of the skin lesion.

Color enhancement techniques are used to adjust the color balance and saturation of the image. Color balance adjustment can be achieved by adjusting the color channels of the image, while saturation adjustment can be achieved by adjusting the intensity of the color channels. Color correction techniques, such as gray world and white balancing Barata et al. [22], can also be used to adjust the color balance of the image.

### 3.2 Feature extraction

Feature extraction techniques involve identifying specific features of the skin image that are relevant to the analysis task. These features can be morphological Mishra et al. [73], textural, or spectral, and can be extracted using various techniques such as edge detection, segmentation, and texture analysis. Bansal et al. [21] propose the use of integrated features that are extracted using handcrafted feature extraction techniques and deep learning models to enhance the performance of classifier.

#### 3.2.1 Traditional approaches of feature extraction

Traditional approaches include Handcrafted feature extraction techniques Arasi et al. [15], Javed et al. [51] involve designing specific features or descriptors that are tailored to a particular task or domain, such as texture, shape, or color-based features. Examples of handcrafted features include Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP) Senan and Jadhav [97], Khanvilkar and Bhatt [60], and Scale Invariant Feature Transform (SIFT) Rahman et al. [86]. Machine learning and deep learning Bechelli and Delhommelle [23] have transformed feature extraction by automating the process and enabling the discovery of more intricate and sophisticated features. In contrast, traditional handcrafted feature extraction techniques rely on domain knowledge and expert-defined feature engineering. With machine learning, the features are learned from the data itself, eliminating the need for manual feature engineering Saba [91].

#### 3.2.2 Deep learning-based feature extraction

Deep learning-based feature extraction techniques learn features automatically from data using neural networks, such as Convolutional Neural Networks (CNNs) Seeja and Suresh

[95],Yao et al. [122]. The advantage of deep learning-based techniques is that they can learn high-level abstract features that are more effective than handcrafted features in many applications. However, deep learning-based techniques require large amounts of training data and significant computational resources for training and inference. Handcrafted feature extraction techniques, on the other hand, are more interpretable and require less data and computational resources, but may not perform as well as deep learning-based techniques in some cases Singh et al. [104]. Hybrid techniques for feature extraction leverage the advantages of both traditional handcrafted features and deep learning-based features to develop a more comprehensive and potent representation of skin images. By combining the outputs of diverse feature extraction approaches, the hybrid model can encompass a broader spectrum of image characteristics and patterns, resulting in feature representations that are more resilient and informative Mahbod et al. [67].

The extracted features can then be used to train classification algorithms such as decision trees, support vector machines, and neural networks Seeja and Suresh [95] Murugan et al. [75]. These algorithms use the extracted features to classify the skin images into different categories such as normal skin, benign skin lesions, and malignant skin lesions. One of the advantages of conventional image processing techniques is that they are relatively simple and computationally efficient Sreedhar et al. [107]. Additionally, they do not require large amounts of data to train the algorithms. However, one of the limitations of these techniques is that they rely heavily on the quality of the extracted features, which can be influenced by various factors such as lighting conditions and image artifacts. In recent years, the use of deep learning techniques has gained popularity in skin image analysis due to their ability to automatically learn relevant features from the raw data Yao et al. [122],Singh et al. [104]. However, conventional image processing techniques still have a role to play in skin image analysis, especially in cases where limited data is available or when interpretability is important. Therefore, a combination of conventional image processing techniques and deep learning techniques can be used to achieve the best results in skin image analysis Rahman et al. [86],Moussaoui et al. [74].

Table 1 presents the various feature extraction techniques surveyed. Figure 5 depicts the Accuracy of the various feature extraction techniques summarized in Table 1. The technique proposed by Akram et al. [12] gives the highest accuracy of 98.8%, followed by Hagerty et al. [41] at 94%, Seeja and Suresh [95] at 85.19% and Riaz et al. [89] at 84%.

### 3.3 Segmentation techniques

Image segmentation involves dividing an image into multiple segments or regions, each of which corresponds to a specific object or structure. In dermatology, image segmentation is used to identify different structures within the skin, such as the epidermis, dermis, and subcutaneous tissue.

Segmentation techniques are used to partition the image into regions of interest, such as skin lesions or healthy skin regions. Common segmentation techniques used in skin image analysis include thresholding, region growing, watershed segmentation, and Active-contour based segmentation Wang et al. [116], Mirikharaji et al. [72].

#### 3.3.1 Thresholding

Thresholding is a basic image processing technique that involves converting Khan et al. [57] Pereira et al. [85] grayscale image into a binary image by defining a threshold value that separates foreground and background pixels. Hu et al. [48] have proposed a two-step method combining saliency detection and adaptive thresholding based on wavelet transform in order to obtain more accurate lesion regions. The paper evaluates the proposed method on two datasets of dermoscopy images and compares it with seven other methods.

**Table 1** Summary of feature extraction techniques

| Authors | Disease | Technique | Dataset | Description |
|---|---|---|---|---|
| Riaz et al. [89] | Melanoma | Handcrafted | PH2, [3] | KL divergence, Image features using local binary patterns |
| Seeja and Suresh [95] | Melanoma | U-net | [2] | Segmentation: U-net, Feature extraction: local binary pattern, edge histogram, histogram of oriented gradients and Gabor method, classification: support vector machine, random forest, KNN and Na¨ıve Bayes |
| Hagerty et al. [41] | Melanoma | Resnet50 | Private dataset, HAM10000 | Combines conventional image processing with deep learning to classify dermoscopy images of skin lesions as melanoma or benign |
| Akram et al. [12] | Melanoma | DenseNet 201, Inception-ResNet-v2, and Inception-V3 | PH2, [3] | Feature fusion from DenseNet 201, inception-ResNet-v2, and Inception-V3. Hierarchical architecture for feature selection and dimensionality reduction |

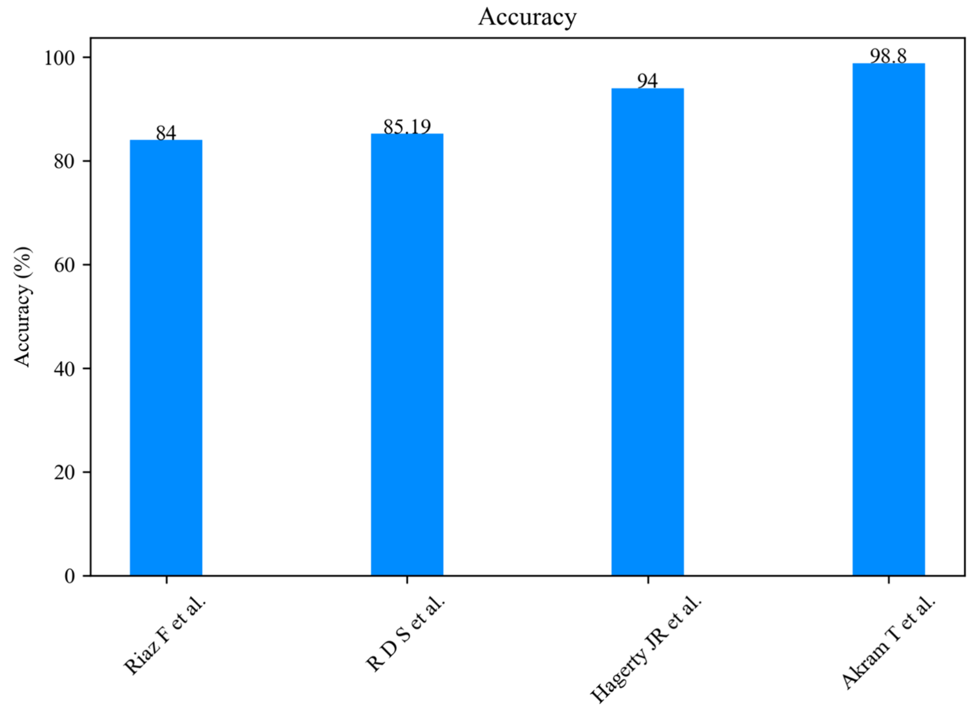


**Fig. 5** Accuracy of various feature extraction techniques

#### 3.3.2 Edge detection

Edge Detection: Edge detection is a common image processing technique used to identify boundaries between different regions in an image. Sengupta et al. [99] have proposed a three-stage preprocessing approach to enhance the quality of the skin lesion image. This includes color space transformation, contrast enhancement, and applying filtering techniques. Next, an edge map is generated using three well-known edge detection methods: Canny, Sobel, and Prewitt. Ant Colony Optimization (ACO) is applied on these edge maps in order to improve the edge contours.

#### 3.3.3 Region growing

Region growing is a technique used for image segmentation where pixels in an image are grouped into meaningful regions based on certain similarity criteria. Namboodiri and Jayachandran [76] have suggested that skin lesion classification requires considering multiple dimensions and nonlinear aspects. To address this, they introduce a new and innovative approach that utilizes a Deep Convolutional Neural Network (DCNN). Before feeding the skin lesion images to the DCNN, they apply an automatic preprocessing algorithm along with a fusion hair detection and removal strategy to ensure the images are ready for analysis. To further improve the classification process, they incorporate a new probability map-based region growing and optimal thresholding algorithm into the system. This combination of techniques aims to achieve more accurate and effective skin lesion classification. Bama et al. [19] have proposed a methodology that involves utilizing Gaussian Mixture Model superpixels to segment candidate images into homogeneous regions, accurately isolating the melanoma region.

#### 3.3.4 Active-contour based

Region-based active contour segmentation is a popular technique used in skin image segmentation. In this method, an initial contour is defined around the region of interest, and then the contour is iteratively adjusted to fit the boundaries of the object being segmented. Riaz et al. [89] have proposed a novel active contours-based segmentation method that leverages the Kullback–Leibler divergence to fit a curve to the lesion boundaries, effectively delineating the skin lesions. Kowsalya et al. [62] have proposed a method for evaluating skin melanoma using the Chan-Vese (CV) segmentation technique Chan and Vese [25]. They conduct their study using the widely recognized ISBI 2016 grand-challenge dataset. At first, the CV segmentation is directly applied to the image to extract the affected skin region. This section is then compared to the Ground-Truth (GT) picture to assess the accuracy of the CV segmentation. To further improve the process, they implement a two-level procedure that combines thresholding based on the Jaya Algorithm (JA) Rao [87] and Tsal-lis Entropy Tsallis [113] (JA + TE) with the CV segmentation. The resulting skin section is once again compared to the GT, and the Picture-Similarity-Measures (PSM) are computed. The outcomes of their experiments indicate that the two-level procedure yields better PSMs compared to the single-step approach relying solely on CV segmentation.

### 3.3.5 Semantic segmentation

In the realm of computer vision and image analysis, one vital task is semantic segmentation, where the goal is to assign meaningful labels to every pixel in an image, effectively dividing it into distinct regions. Two popular architectural approaches for this purpose are SegNet Han et al. [42] and hybrid CNN-RNN networks Al-Masni et al. [13]. SegNet is engineered as a convolutional neural network (CNN) that specializes in semantic segmentation duties. Its design revolves around an encoder-decoder framework, with the encoder extracting hierarchical features from input images, and the decoder generating pixel-level segmentation maps. This architecture has gained traction due to its simplicity and efficiency, proving its worth across various applications. On the other hand, hybrid CNN-RNN networks blend the strengths of convolutional neural networks (CNNs) for feature extraction with recurrent neural networks (RNNs) for capturing spatial relationships and context. By fusing CNNs and RNNs, these hybrid models achieve more precise segmentation outcomes, particularly in tasks where understanding spatial context is crucial, such as medical image analysis and scene comprehension. Overall, approaches leveraging architectures like SegNet and hybrid CNN-RNN networks show promising results in semantic segmentation, marking significant strides in computer vision and image analysis research.

Akram et al. [11] present a novel approach to skin lesion analysis within the IoMT framework. By leveraging cutting-edge techniques such as Mask Region-based Convolutional Neural Network (MRCNN) for semantic segmentation and ResNet50 for lesion detection, their hybrid deep learning model demonstrates remarkable performance. The study underscores the potential of their hybrid deep learning strategy to advance skin lesion analysis, offering superior performance compared to existing standards and paving the way for enhanced diagnostic capabilities in IoMT applications.

Öztürk and Özkaya [83] address the growing challenge of skin cancer detection by presenting an effective segmentation method based on a fully convolutional network (FCN). Their proposed improved FCN (iFCN) architecture enhances the segmentation of full-resolution skin lesion images, overcoming issues such as indistinct boundaries and color differences. By incorporating spatial information to support the residual structure of the FCN architecture, the iFCN method enables precise detection of lesion details and offers contributions in determining lesion centers and clarifying edge details.

Figure 6 shows the various Image Segmentation techniques. Figure 6a and b are the input images, and Fig. 6d

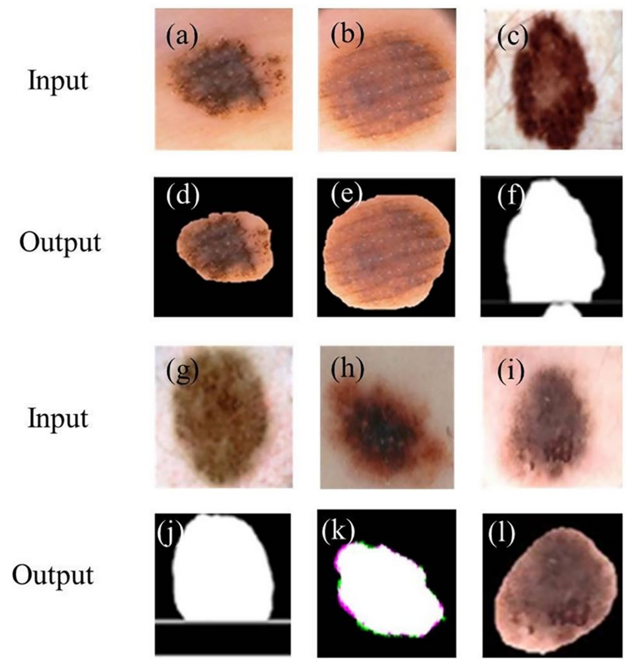


**Fig. 6** Various segmentation techniques. **a–c** and **g–i** are input images, **d–f** and **j–l** are output images

and e are the output images of the methodology based on the YOLO and Grabcut methods of image segmentation proposed by Ünver and Ayan [115]. Figure 6c and g are the input images, Fig. 6f and j are the segmented images using the GA-net proposed by Zhou et al. [127]. Figure 6h is the input image and Fig. 6k is the segmented image using an ensemble approach for segmentation proposed by Tamoor et al. [110]. Figure 6i is the input image and Fig. 6l is the segmented image using the FCN-AlexNet framework proposed by Nancy et al. [77].

Table 2 summarizes the various segmentation techniques surveyed in this paper.

Figure 7 depicts the Accuracy of the various segmentation techniques summarized in Table 2. A comparison of the Accuracy is drawn. The technique proposed by Khan et al. [59] gives the highest accuracy at 98.7% as compared to techniques proposed by other researchers.

Figure 8 depicts the Sensitivity, Specificity, Dice coefficient and Jacard Index of the various segmentation techniques summarized in Table 2. The technique proposed by Xie et al. [120] consisting of coarse segmentation network, mask-guided classification network, and enhanced segmentation network outperforms the other techniques proposed in terms of Sensitivity 96.7%, Dice-coefficient 94.2%, and Jacard Index at 89.4%. The technique proposed by Cao et al. [24] has a Specificity of 97.36%.

**Table 2** Summary of segmentation techniques

| Authors | Disease | Technique | Dataset | AUC | Description |
|---|---|---|---|---|---|
| Serte and Demirel [100] | Melanoma, Seborrheic Keratosis | Gabor wavelet | [3] | Melanoma: 96%, SK: 86% | Ensembel of seven gabor wavelets |
| Unver and Ayan [115] | Melanoma | YOLO and Grabcut | PH2, [3] | – | Combining YOLO and Grabcut for skin lesion segmentation |
| Tang et al. [111] | Melanoma | U-net | [2, 3], PH2 | – | Separable U-net with stochastic weighted averaging |
| Riaz et al. [89] | Melanoma | Active contours | PH@, [3] | – | KL divergence, image features using local binary patterns |
| Seeja and Suresh [95] | Melanoma | U-net | [2] | – | Segmentation: U-net, feature extraction: local binary pattern, edge histogram, histogram of oriented gradients, Gabor method, classification: support vector machine, random forest, KNN and Naïve Bayes |
| Garcia-Arroyo and Garcia Zapirain [32] | Melanoma | Histogram, thresholding | [2, 3] | – | Skin lesion segmentation using fuzzy classification of pixels and histogram thresholding |
| Song et al. [106] | Melanoma | R-CNN, U-net | [2, 3] | – | Faster R-CNN for detection/classification U-net for segmentation |
| Wang et al. [118] | Melanoma | CNN | [2, 3] | – | Bi-directional dermoscopic learning (biDFL) framework models complex correlation between skin lesions and their informative context, multiscale consistent decision fusion (mCDF) for informative decisions generated from multiple classification layers |
| Goyal et al. [36] | Skin cancer | Mask R-CNN, DeeplabV3+ | PH2, [3] | – | Combine Mask R-CNN and DeeplabV3+ models |
| Hasan et al. [44] | Skin cancer | U-net, FCn | PH2, [3] | 87% | Automatic sematic segmentation network |
| Xie et al. [120] | Skin cancer | CNN | PH2, [3] | – | Consists of coarse segmentation network, mask-guided classification network, enhanced segmentation network |
| Khan et al. [58] | Skin cancer | CNN | [2–4], PH2, HAM10000 | – | Framework for skin lesion detection and classification consisting of two modules: lesion localization/segmentation and classification |
| Khan et al. [59] | Skin cancer | CNN | [2–4], PH2, HAM10000 | – | Image enhancement, saliency of lesion regions, conversion to binary image, feature extraction, feature fusion classification |

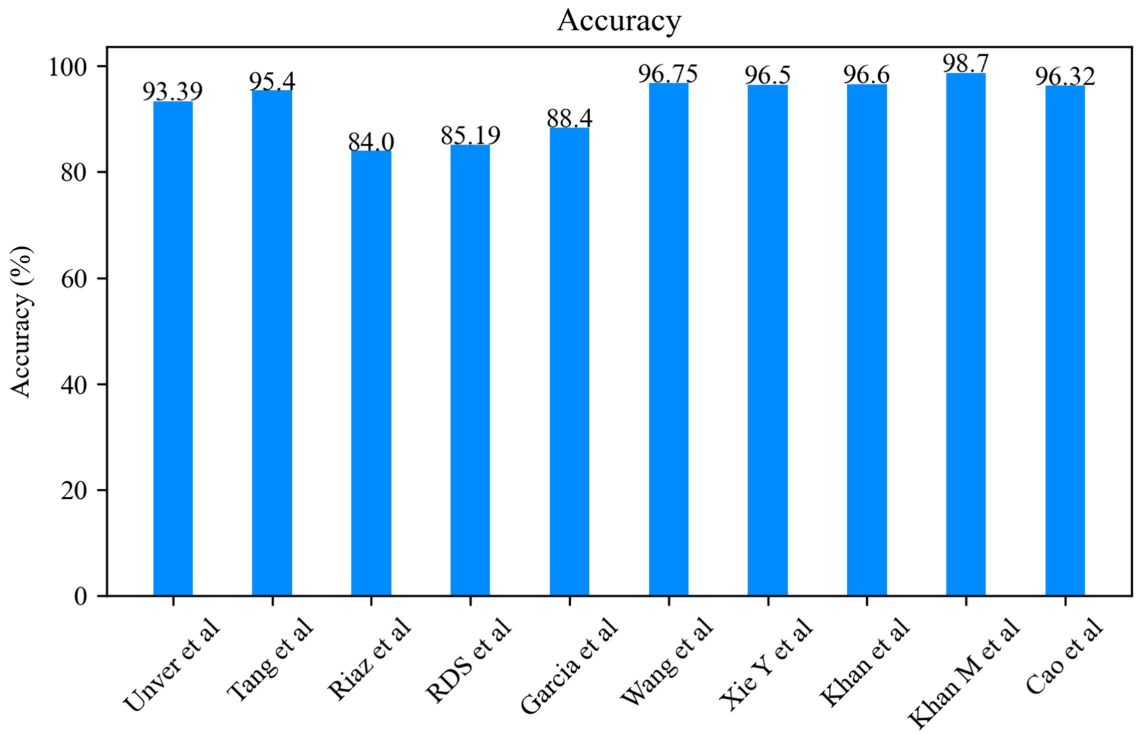


**Fig. 7** Accuracy of various segmentation techniques

### 3.4 Classification techniques

Image classification is a fundamental task in image processing and involves categorizing an image into predefined classes or labels. Classification techniques are used to classify the skin image or its features into different categories or classes based on predefined criteria, such as disease type or severity Solatidehkordi and Zualkernan [105]. These techniques have been used in both conventional image processing and in Machine Learning and Deep Learning-based approaches, which have led to significant progress in the field of skin image analysis Arasi et al. [15],Mahbod et al. [67],Albahar [14],Shetty et al. [103],Esteva et al. [30].

The objective of image classification is to teach a model to recognize key features that distinguish different image classes and accurately classify new, unseen images Maron et al. [70],Hosny et al. [47].

#### 3.4.1 Traditional approaches

Traditional methods for image classification typically involve handcrafting features, where a set of predefined characteristics is designed based on prior knowledge of the problem domain Sekhar et al. [96]. These features can include texture, color, shape, and other visual aspects relevant to the image classification task. Some common techniques for feature extraction include detecting edges, segmenting regions, and using statistical measures like histograms and moments. However, these traditional approaches have limitations when it comes to capturing complex and high-level features that are crucial for accurate classification.

#### 3.4.2 Deep-learning based

In recent times, the field of image classification has witnessed groundbreaking advancements in machine learning and deep learning. This has led to the creation of models like convolutional neural networks (CNNs) that can automatically learn features directly from raw image data. These methods have proven to be highly effective in a wide range of image classification tasks, including skin image analysis Sharafudeen [101]. However, they often require substantial amounts of labeled data and significant computational resources for training, making them less accessible for certain applications.

Table 3 summarizes the various classification techniques surveyed in this paper. Figure 9 plots accuracy of the classification techniques summarized in Table 3.

The technique proposed by Okuboyejo and Olugbara [82] that combines residual network (ResNext) and the dual path network with confidence preservation (DPN-CP) has the highest accuracy of 98.54%.

Figure 10 plots AUC, Sensitivity, Specificity and F1 score of the classification techniques summarized in Table 3. The

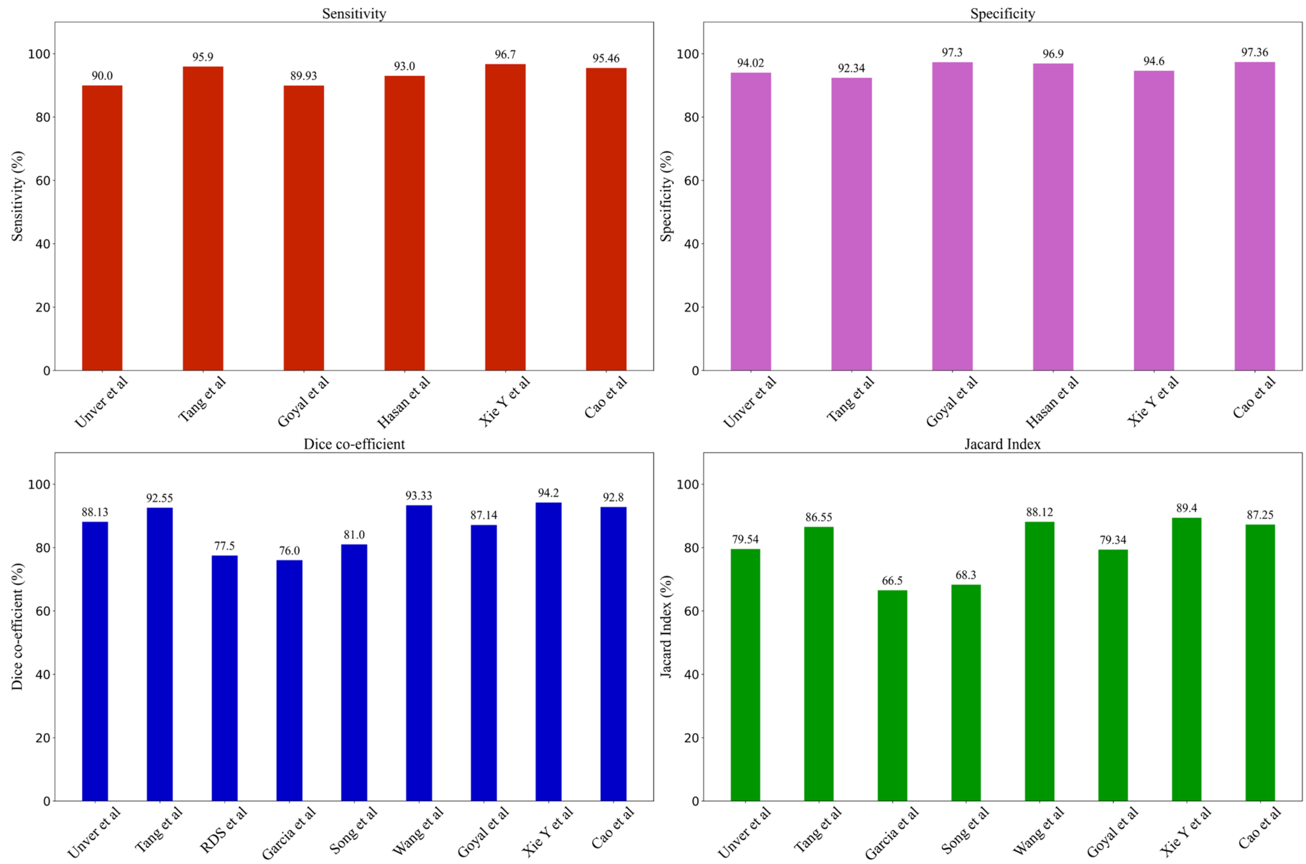


**Fig. 8** Sensitivity, specificity, dice co-efficient and Jacard Index of various segmentation techniques

technique proposed by Albahar [14] has the highest AUC of 98%, and the technique proposed by Hosny et al. [47] has the highest Sensitivity of 97.34%. The technique proposed by Okuboyejo and Olugbara [82] has a Specificity of 99% and that proposed by Ahammed et al. [9] has F1-score of 94.88%.

### 3.5 Recent surveys in skin image analysis

The landscape of skin image analysis has been significantly shaped by recent sur veys, which illuminate key themes and advancements in this critical field of medical diagnostics:

**Diagnostic Challenges and Traditional Methods:** Skin diseases present formidable diagnostic challenges due to their diverse manifestations and the subjective nature of visual inspection Nancy et al. [78]. Traditional diagnostic methods heavily rely on manual examination by dermatologists, which can be time-consuming and subject to variability among practitioners.

**Technological Advancements:** Recent years have witnessed a notable surge in ML and DL techniques Tiwari et al. [112], particularly CNNs aimed at automating the diagnosis of skin diseases Yadav and Bhat [121]. These advanced techniques excel in extracting intricate features from skin lesion images Sauter et al. [93], significantly enhancing both diagnostic accuracy and efficiency.

**Application Areas:** The focus of research spans a broad spectrum of skin diseases, encompassing conditions such as melanoma, basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and various other dermatological disorders. The primary emphasis is on early detection, crucial for improving treatment outcomes and reducing mortality rates associated with these diseases.

**Methodologies and Algorithms:** Key methodologies include essential preprocessing steps such as image enhancement, noise reduction, and segmentation, vital for optimizing image quality and extracting relevant features Nugroho et al. [81]. DL models, especially CNNs, are prominently utilized for their capability to learn hierarchical representations directly from images, enabling effective disease classification Sun et al. [109]. Performance evaluation metrics such as accuracy, sensitivity, specificity, Area Under the Curve (AUC), and Dice similarity coefficient are commonly employed to assess the efficacy and reliability of these models.

**Table 3** Summary of classification techniques

| Authors | Disease | Technique | Dataset | Description |
|---|---|---|---|---|
| Hosny et al. [47] | Skin cancer | Alex-net | Mednode, Derm, ISIC | Alex-net for classification, dataset augmented by fixed and random rotations |
| Albahar et al. [14] | Melanoma | CNN | [4] | Binary classifier uses regularizer technique based on standard deviation of weight matrix of classifier |
| Zhang et al. [126] | Melanoma, Seborrheic Keratosis, Nevus | ARL- CNN | [3] | Residual learning and attention learning mechanisms |
| Song et al. [106] | Melanoma | R-CNN, U-net | [2, 3] | Faster R-CNN for detection/classification, U-Net for segmentation |
| Xie et al. [120] | Skin cancer | CNN | PH2, [3] | Three networks: coarse segmentation, mask-guided classification, enhanced segmentation network |
| Gessert et al. [34] | Skin cancer | CNN | HAM10000 | Patch-based attention architecture |
| Khan et al. [58] | Skin cancer | CNN | [2–4], PH2, HAM10000 | Two modules: lesion localization/segmentation and classification |
| Khan et al. [59] | Skin cancer | CNN | [2–4], PH2, HAM10000 | Image enhancement, saliency of lesion regions, conversion to binary image, feature extraction, feature selection, feature fusion, classification |
| Ahammed et al. [9] | Skin lesion | Gaussian filtering, Grabcut, GLCM, Decision Tree, SVM, KNN | [5], HAM10000 | Preprocessing: Gaussian filtering, segmentation: Grabcut, feature extraction: GLCM, classification: decision tree, SVM, KNN |
| Yao et al. [122] | Skin cancer | DCNN | [3–5] | Single-model based strategy for classification of skin lesions on small and imbalanced datasets |
| Yue et al. [124] | Skin cancer | CNN | [4, 5] | Solution for multi-center skin lesion classification using deep neural networks with adaptively weighted balance loss |
| Lee et al. [63] | Rosacea, dermatitis | CNN | Private dataset | Mobile diagnosis of skin diseases using a smartphone-based fluorescence imaging system |
| Okuboyejo and Olugbara [82] | Skin lesion | CNN | [2–6] | Combines residual network with next dimension (ResNeXt) and the dual path network with confidence preservation (DPN-CP) |

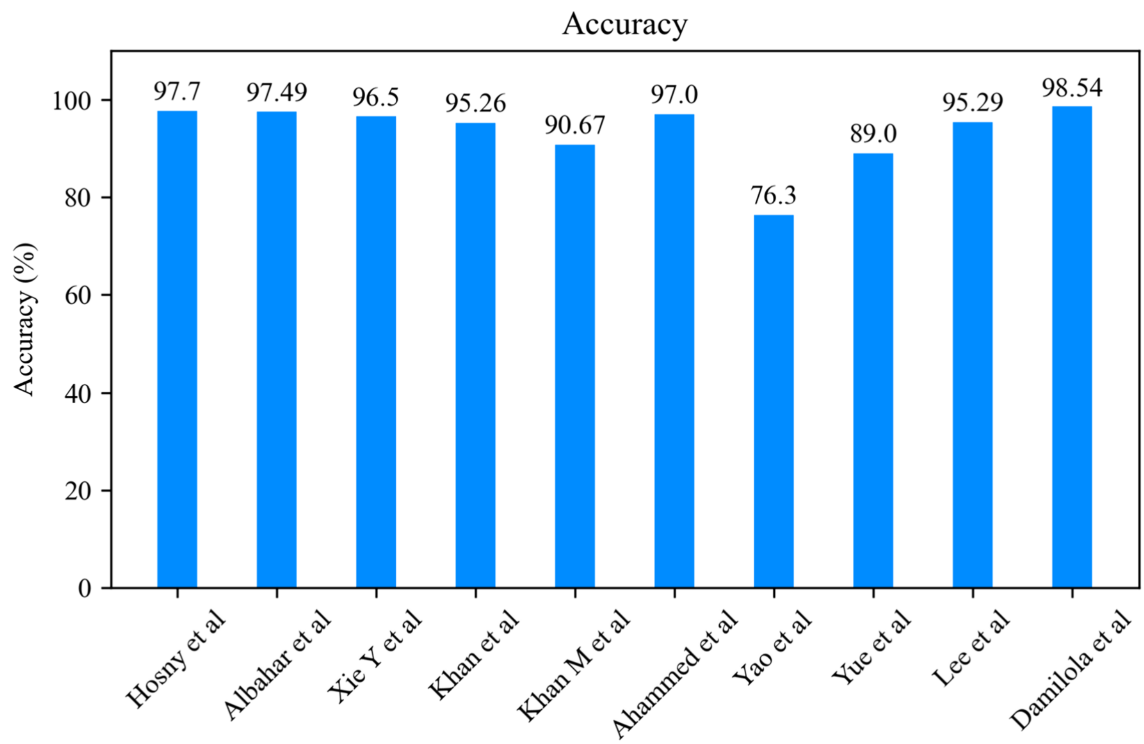


**Fig. 9** Accuracy of various classification techniques

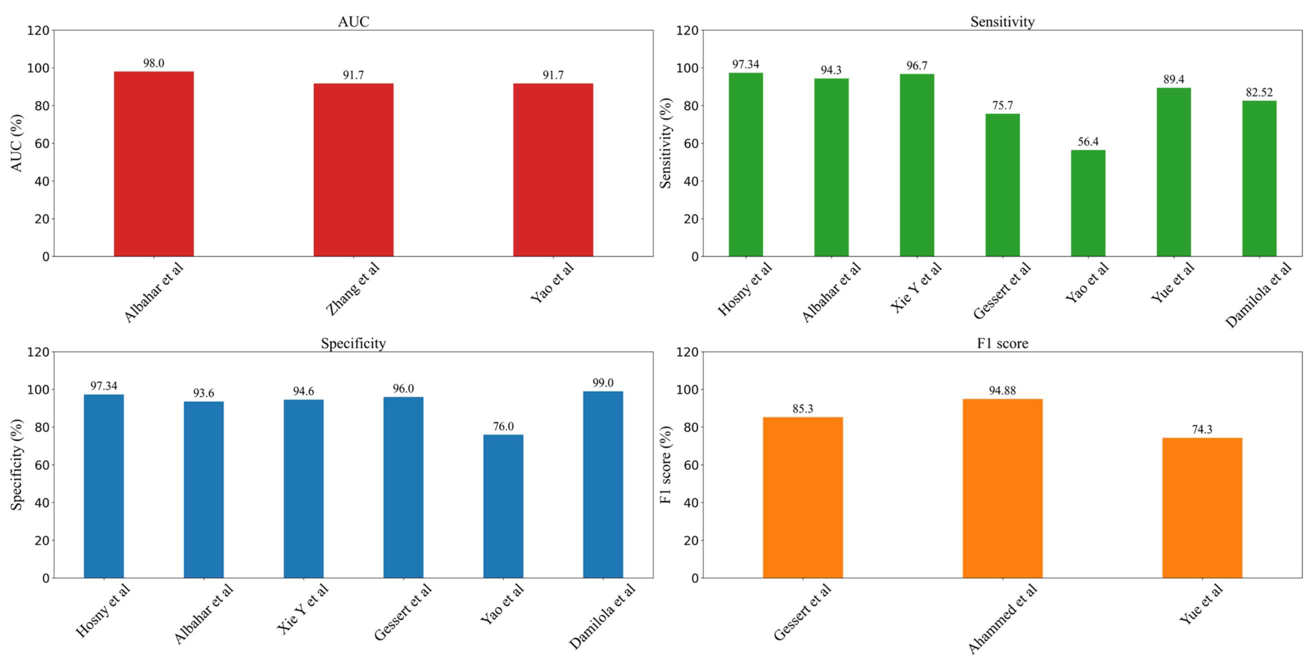


**Fig. 10** AUC, sensitivity, specificity and F1 score of the various classification techniques

**Dataset Utilization:** Benchmark datasets like ISIC, PH2, HAM10000 and Dermnet, play a crucial role in training and evaluating skin disease detection models, ensuring the robustness and generalizability of models across diverse populations and skin types. The details of these datasets have been presented in Sect. 5 of this paper.

### 3.6 Ethical Considerations and Challenges:

Ethical considerations in handling medical image datasets include ensuring patient privacy and data security. Challenges in the field encompass issues related to dataset variability, model interpretability, and the generalization of AI models across different patient demographics and skin types.

**Future Directions:** Future research directions are expected to focus on enhancing the interpretability and explainability of DL models, addressing performance disparities across underrepresented skin types, and integrating multimodal imaging techniques to further augment diagnostic accuracy Grignaffini et al. [37].

**Recent Surveys in analysis of Skin Images for disease diagnosis:** Recent surveys underscore the effectiveness of deep learning architectures such as CNNs, ResNets, and ensemble models in classifying skin lesions and detecting melanoma from dermoscopic images Gayatri and Aarthy [33]. Advanced techniques like transfer learning, region-based CNNs, and attention mechanisms have been explored to refine feature extraction and disease localization.

**Performance Benchmarking:** Performance evaluations across multiple datasets continue to serve as benchmarks for comparing different algorithms, utilizing metrics such as sensitivity, specificity, and AUC to gauge the robustness and reliability of automated diagnostic systems Mirikharaji et al. [72].

**Emerging Challenges and Opportunities:** Emerging challenges include addressing dataset biases, improving model generalization across diverse populations, and ensuring the ethical use of patient data. Opportunities for advancement include developing interpretable DL models, leveraging federated learning for collaborative model training Yaqoob et al. [123], and expanding research efforts into rare and less common skin conditions Choy et al. [26].

**Clinical Adoption and Impact:** Insights into the clinical adoption of automated systems underscore their potential to alleviate healthcare burdens, expedite diagnostic processes Hasan et al. [45], and potentially reduce healthcare costs. Continued collaboration between researchers, clinicians, and industry stakeholders will be pivotal in translating research innovations into practical clinical applications Grignaffini et al. [37].

In conclusion, recent surveys in skin image analysis highlight the transformative impact of deep learning and machine learning technologies on dermatological diagnostics. These advancements not only enhance diagnostic accuracy but also pave the way for personalized medicine approaches, significantly improving outcomes in the management of various skin diseases.

## 4 Machine learning and deep learning in skin image analysis

Adegun and Viriri [8] have introduced a novel framework designed to automate the segmentation and classification of skin lesions for detecting skin cancer. This framework operates in two stages: firstly, utilizing an encoder-decoder Fully Convolutional Network (FCN) to capture intricate and heterogeneous features of skin lesions. The encoder phase focuses on learning coarse appearances, while the decoder phase hones in on details of lesion borders. In the second stage, they propose a novel FCN-based DenseNet framework featuring dense blocks interconnected through concatenation strategies and transition layers. The system incorporates hyper-parameter optimization techniques to streamline network complexity and enhance computational efficiency. This approach encourages feature reuse, resulting in a reduced parameter count and efficacy even with limited data.

Karthik et al. [55] have proposed a skin disease detection system using a convolutional neural network (CNN) that can classify four different skin conditions: acne, actinic keratosis (AK), melanoma, and psoriasis have proposed a convolutional neural network (CNN) named Eff2Net has been developed for classifying four distinct skin conditions: acne, actinic keratosis (AK), melanoma, and psoriasis. Built upon the EfficientNetV2 architecture, Eff2Net integrates an Efficient Channel Attention (ECA) block, which replaces the standard Squeeze and Excitation (SE) block, thereby significantly reducing trainable parameters without compromising accuracy. EfficientNetV2, renowned for its optimized balance between precision and efficiency, is enhanced by the ECA block's ability to selectively attend to informative channels while suppressing irrelevant ones. This attention mechanism elevates feature representation and boosts model discriminability. Experimental validation on a dataset containing diverse skin images yielded an impressive overall testing accuracy of 84.70%, aligning competitively with state-of-the-art deep-learning methods in existing literature. Moreover, Eff2Net showcases superior computational efficiency owing to its minimized parameter load compared to other deep learning models.

In their work, Esteva et al. [30] demonstrated the efficacy of a deep convolutional neural network (CNN) in automating the classification of skin lesions using clinical images. Trained on a dataset comprising 129,450 clinical

**Table 4** Summary of detection techniques

| Authors | Disease | Technique | Dataset | Description |
|---|---|---|---|---|
| Song et al. [106] | Melanoma | R-CNN, U-net | [2, 3] | Faster R-CNN for detection/ classification, U-net for segmentation |
| Wei et al. [119] | Skin cancer | U-net | [2] | Two feature extraction modules, a feature discrimination network, and a model fusion strategy |
| Kadampur and Riyaee [53] | Skin cancer | DLS | HAM10000 | Model-driven architecture in the cloud uses deep learning algorithms to construct models |
| Pacheco and Krohling [84] | Skin cancer | Clinical data | Private dataset | Dataset of clinical images using smartphones, clinical data of patients, combine features from both |
| Zhang et al. [125] | Melanoma | CNN | Private dataset | Siamese neutral network for detecting short- term changes in skin lesions |
| Leite et al. [64] | Skin detection | CNN | Private dataset | Segmentation and quantification of skin pixels based on ROI |
| Ahammed et al. [9] | Skin lesion | ML/ DL | [5], HAM10000 | Preprocessing: Gaussian Filtering, Segmentation: Grabcut, Feature extraction: |
| Nauta et al. [79] | Skin cancer | Image inpainting | HAM10000 | Shortcut learning using inpainting techniques |
| Wang et al. [117] | Skin cancer | CNN | HAM10000 | Multimodal CNN of image data, metadata of patients, and domain knowledge |
| Ain et al. [10] | Skin cancer | Genetic Programming | Dermofit, PH2 | Automatic diagnosis on multimodality images |
| Li et al. [65] | Skin cancer | CNN | [5], DermNet | Out-of- distribution detection based on Deep Neural Forests (DNF) |
| Liu et al. (2023) | Skin cancer | CNN | [2–6] | Four modules: lesion area attention, feature extraction, lesion feature attention, and distinguish module |
| Baig et al. [17] | Skin cancer | CNN | [5, 6], HAM10000 | Light-dermo based on ShuffleNEt architecture, incorporates channelwise attention mechanism |
| Gupta et al. [38] | Skin diseases | Gaussian Mixing Model | Dermnet NZ | GMM for analyzing and identifying diseases with GLCM derived from images input |
| López-Leyva et al. [66] | Skin lesion | CNN | HAM10000 | Fourier spectral information of images on an additive color model |

images across 2,032 different diseases, the CNN underwent rigorous testing against evaluations by 21 board-certified dermatologists using biopsy-proven clinical images. The CNN exhibited comparable performance to dermatologists in distinguishing keratinocyte carcinomas from benign seborrheic keratoses, as well as malignant melanomas from benign nevi. This capability suggests that AI-powered systems could potentially extend dermatological diagnostic capabilities beyond traditional clinical settings, offering cost-effective and universally accessible diagnostic solutions.

Table 4 summarizes the various skin disease detection techniques surveyed in this paper.

Figure 11 plots accuracy of the disease detection techniques summarized in Table 4. The technique proposed by L´opez-Leyva et al. [66] involving Fourier spectral information of images on an additive color model has the highest accuracy of 99.33%. Figure 12 plots AUC, sensitivity, specificity and F1 score of the disease detection techniques summarized in Table 4. The technique proposed by López-Leyva et al. [66] has a Specificity of 99.63%. The technique proposed by Baig et al. [17] gives Sensitivity and F1-score of 97.45% and 98.1% respectively. The technique proposed by Kadampur and Riyaee [53] gives the highest accuracy at 99.77%.

Figure 13 plots precision and recall of the disease detection techniques summarized in Table 4. The technique proposed by Ahammed et al. [9] gives the highest precision at 95.13% and that proposed by Leite et al. [64] gives the highest recall at 95.92%.

## 5 Dataset availability

The availability of publicly available datasets has revolutionized research in the area of skin image analysis by providing researchers with standardized and diverse data for algorithm development, training, and evaluation. These serve as benchmarks for evaluation of algorithms for analysis of skin images. Researchers can use these datasets for training complex deep learning models, leading to improved accuracy and reliability in disease detection and classification. They can compare state-of-the-art methods against their

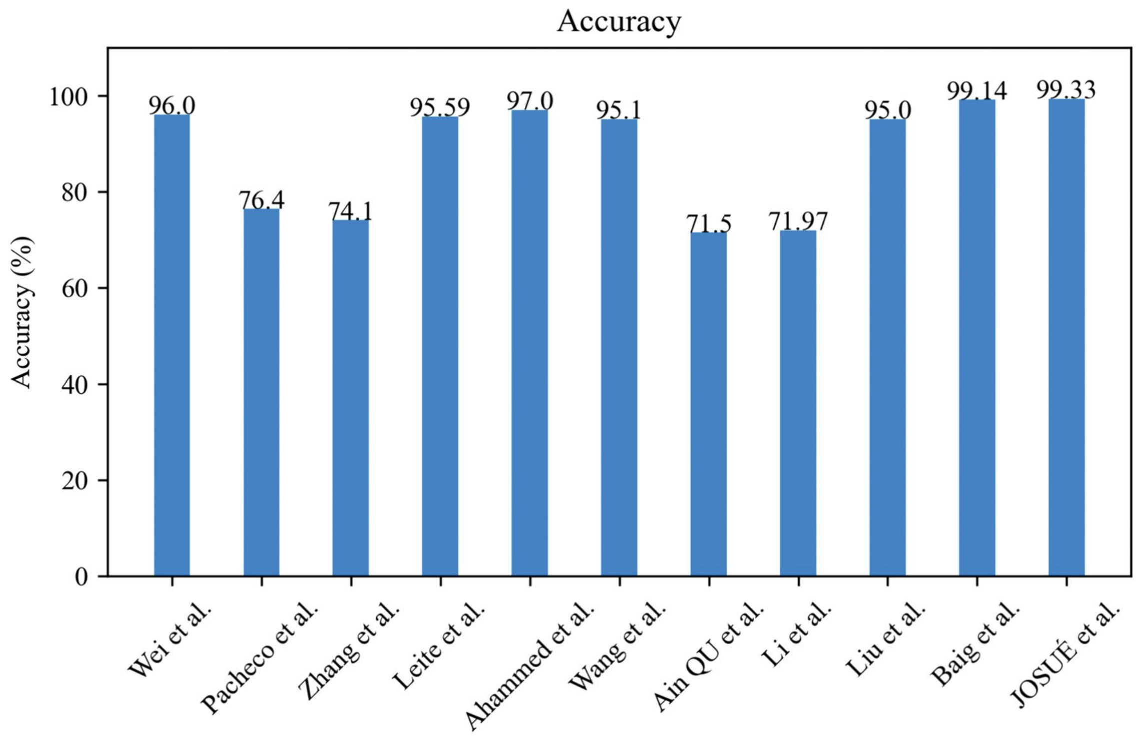


**Fig. 11** Accuracy of various disease detection techniques summarized in this survey

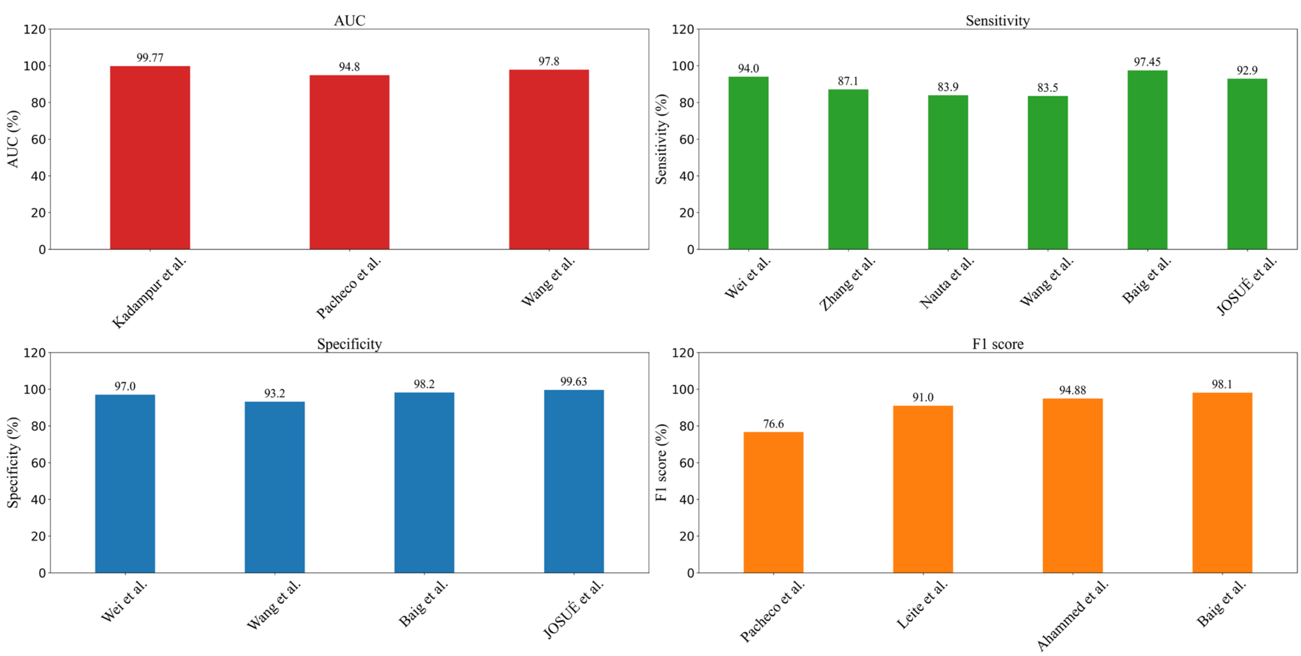


**Fig. 12** AUC, sensitivity, specificity and F1 score of various diseases detection techniques summarized in this survey

models on the same datasets, enabling fair and standardized comparisons. Although these datasets come with challenges like data diversity, unbalanced data, inconsistent annotated data, small sample sizes, and limited domain adaptation, they serve as a basis for providing a platform for exemplifying principles of open science and promoting collaborative efforts to solve critical healthcare challenges.

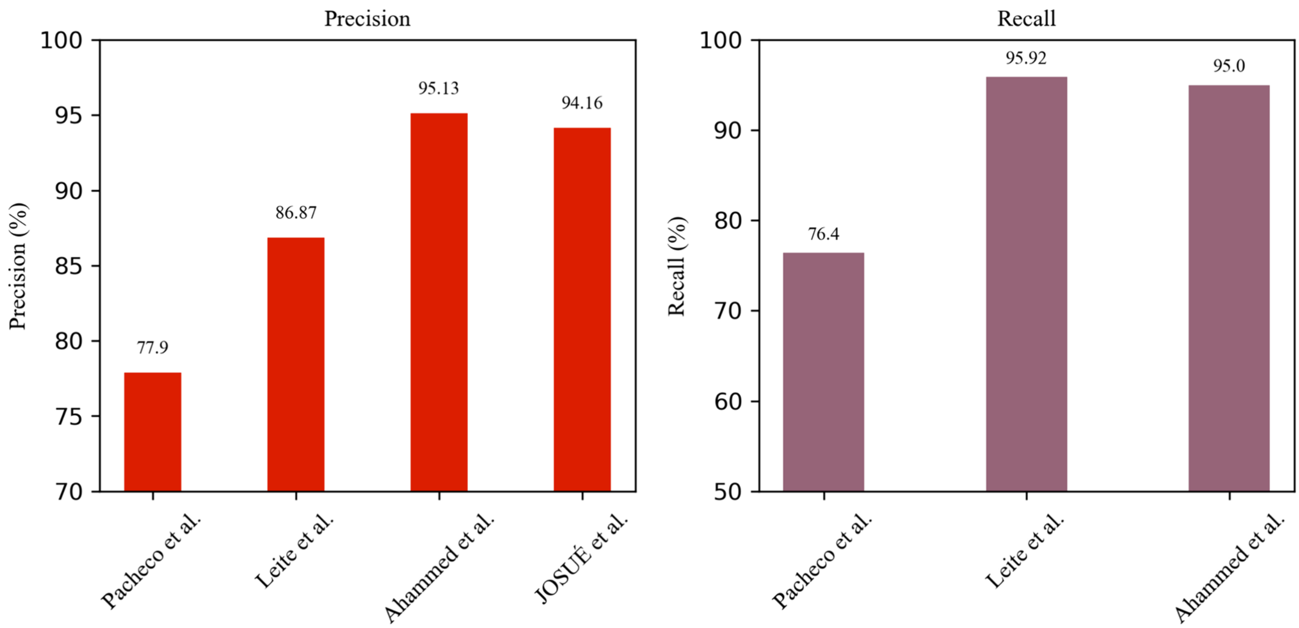


**Fig. 13** Precision and recall of various disease detection techniques summarized in this survey

## 5.1 Types of images in datasets

Publicly available datasets for skin image analysis typically include various types of images, each serving specific purposes in dermatological research. Some common types of images found in these datasets are:

1. Dermoscopic Images: Dermoscopic images are captured using a dermoscope, a specialized device that allows for magnified visualization of skin lesions. These images provide detailed insights into the surface and subsurface structures of skin lesions, aiding in the diagnosis of various dermatological conditions.
2. Clinical Images: Clinical images are photographs taken using standard digital cameras or smartphones. These images offer a broader view of skin lesions and are often used for general assessment and documentation purposes in clinical settings.

## 5.2 Process of creating a dataset

Creating datasets for skin image analysis typically involves several steps:

- Data Collection: The first step is to collect skin images from various sources such as hospitals, clinics, research institutions, or publicly available repositories. These images may include dermoscopic images, clinical photographs, histopathological slides, or other types of skin images.
- Annotation: Once collected, the images need to be annotated by experts to provide ground truth labels for training machine learning algorithms. Annotation involves identifying and labeling regions of interest within the images, such as lesions, healthy skin areas, or specific structures like hair or ruler marks.
- Preprocessing: Preprocessing steps may be applied to the images to enhance their quality and standardize their format. This may include resizing, cropping, normalization, noise reduction, or color correction to ensure consistency across the dataset.
- Splitting: The dataset is divided into training, validation, and test sets. The training set is used to train the machine learning models, the validation set is used to tune hyperparameters and monitor performance during training, and the test set is used to evaluate the final performance of the trained models.
- Augmentation: Data augmentation techniques may be applied to increase the diversity of the dataset and improve the generalization ability of the models. Augmentation techniques include rotation, flipping, scaling, cropping, adding noise, or applying other transformations to the images.
- Quality Control: Quality control measures are implemented to ensure the accuracy and reliability of the dataset. This may involve manual inspection of annotated labels, verifying image quality, and addressing any inconsistencies or errors in the dataset.
- Documentation: Detailed documentation is provided for the dataset, including information about the source

**Table 5** Summary of various publicly available datasets

| Dataset | Modality | Number of images |
|---|---|---|
| DermNet NZ [1] | Clinical | |
| Pedro Hispano Hospital (PH2) PH2) Mendon¸ca et al. [71] | Dermoscopy | 200 |
| ISIC 2016 [2] | Dermoscopy | Training: 727 non-melanomas, 173 melanomas, test: 304 non-melanomas, 75 melanomas |
| ISIC 2017 [3] | Dermoscopy | Training: 1, 626 non-melanomas, 374 melanomas, test: 483 non-melanomas, 117 melanomas |
| ISIC 2018 [4] | Dermoscopy | 10,015 |
| ISIC 2019 [5] | Dermoscopy | 25,331 |
| ISIC 2020 [6] | Dermoscopy | 33,126 |
| HAM10000 Tschandl et al. [114] | Dermoscopy | 1113 non-melanomas, 8902 melanomas |

of the images, annotation guidelines, data format, and any preprocessing or augmentation techniques applied. This documentation helps other researchers understand and use the dataset effectively.

Table 5 summarizes the various publicly available datasets.

## 6 Challenges and future research directions

Deep learning has revolutionized medical imaging, achieving state-of-the-art performance in tasks like segmentation, detection, and classification. However, it's important to remember that human expertise remains the gold standard. Deep learning serves as a powerful assistive tool for medical professionals, not a replacement for their critical analysis and interpretation skills.

While deep learning offers immense potential, there are significant challenges to overcome:

**Image Variability:** Skin images can vary greatly in quality, lighting, resolu tion, and noise. Designing algorithms robust to these variations requires advanced techniques for pre-processing, noise reduction, and color normalization.

**Diverse Skin Types:** Differences in skin type and tone can impact image analysis. Bio-inspired color normalization techniques are crucial to address this challenge.

**Data Annotation:** Manually annotating skin lesions is subjective, time-consuming, and expensive. Variations in ground truth labels can significantly impact algorithm training and evaluation.

**Class Imbalance:** The rarity of certain skin conditions creates an imbalance in datasets, potentially biasing algorithms towards the more common classes.

**Model Interpretability:** Deep learning models, despite their power, are often considered"black boxes" due to the difficulty in interpreting their decision-making processes.

**Domain Adaptation:** Models trained on specific datasets might not generalize well to different imaging devices or clinical settings. Domain adaptation techniques are necessary for robust performance across diverse environments.

**Generalizability:** Ensuring algorithms can generalize to unseen skin conditions and diverse patient demographics is crucial for real-world deployment.

**Computational Cost:** Training deep learning models can be computationally expensive, requiring significant hardware resources and expertise.

## 7 Ethical Considerations:

Data privacy, security, and potential biases within datasets raise important ethical concerns that need to be addressed.

**Regulatory Landscape:** Integrating deep learning models into clinical practice requires navigating a complex regulatory landscape, ensuring safety and efficacy.

## 8 Emerging trends in skin image analysis

Skin image analysis is a rapidly evolving field, constantly pushing the boundaries of what's possible. Here, we explore some of the most exciting emerging trends poised to shape the future of this technology:

**Generative Adversarial Networks (GANs) for Data Augmentation:** Generative Adversarial Networks (GANs) have gained traction in augmenting skin image datasets by generating synthetic images that closely mimic real-world variations. In dermatology, where diverse datasets are crucial for training robust models, GANs help address data scarcity and imbalance issues Rashid et al. [88]. By generating realistic variations of skin lesions, GANs enable more comprehensive training of machine learning models, thereby enhancing their generalization capabilities across different skin types and conditions Su et al. [108].

**Explainable AI (XAI) for Trustworthy Diagnostics:** Deep learning models have shown remarkable accuracy, but their "black box" nature can be a barrier to trust in clinical settings. Emerging XAI techniques aim to shed light on the rationale behind model decisions, allowing healthcare professionals to understand how diagnoses are reached Hauser et al. [46]. This transparency fosters trust and empowers clinicians to leverage AI insights alongside their expertise.

**Federated Learning for Data Privacy and Generalizability**: Data privacy concerns are paramount in medical imaging. Federated learning offers a promising solution Yaqoob et al. [123]. In this approach, model training happens on decentralized devices (e.g., smartphones in hospitals), without sharing raw patient data. This protects privacy while enabling collaboration and development of models across diverse populations.

**Fusion for Comprehensive Insights:** Integrating skin images with other data sources is a growing trend. Combining images with clinical metadata (e.g., demographics, medical history), dermoscopy (microscopic examination), and even genetic information can create a more comprehensive picture of a patient's skin health Rotemberg et al. [90]. This multi-modal approach has the potential to improve diagnostic accuracy and personalize treatment plans.

**Focus on Under-represented Skin Types:** Bias in can lead to algorithms for certain skin types. Researchers are increasingly focusing on developing algorithms specifically designed for under-represented skin tones and ethnicities Kinyanjui et al. [61]. This ensures fairness and in AI-powered skin health solutions.

## 9 Conclusion

In conclusion, this research explores the advancements and challenges in skin image analysis using computer vision. By investigating various pre-processing, feature extraction, and classification approaches, the study highlights the potential of AI to improve diagnostic accuracy and efficiency. Publicly available datasets like ISIC Archive and HAM10000 enable researchers to benchmark algorithms, fostering transparency and collaboration.

Despite remarkable progress, challenges in data diversity, annotation consistency, and model interpretability remain. High-quality, well-annotated datasets encompassing various skin conditions are essential for developing robust and generalizable algorithms. Addressing class imbalance and model interpretability is vital for real-world application.

Moving forward, interdisciplinary collaboration among computer vision specialists, dermatologists, and medical professionals is key to advancing skin image analysis. By prioritizing model interpretability, ethical data practices, and domain adaptation, we can integrate these technologies into clinical practice, ultimately improving early detection, diagnosis, and personalized treatment of skin diseases.

This research aims to contribute to the ever-growing knowledge in this field, inspiring future researchers to tackle existing challenges and unlock the full potential of computer vision for enhancing skin health and patient care. Together, we can build on this knowledge, bridge research gaps, and pave the way for the next generation of skin image analysis advancements that benefit patients worldwide.

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**Data Availability** No datasets were generated or analysed during the current study.

## Declarations

**Conflict of interest** The authors declare no competing interests.

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