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A Comprehensive Survey on Skin disease detection using deep learning

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Abstract

Skin disease detection plays a pivotal role in early diagnosis and effective treatment, impacting patient outcomes and healthcare practices. The integration of Deep Learning (DL) techniques has revolutionized the field, enabling accurate and efficient skin disease detection. This review paper presents a comprehensive analysis of the state-of-the-art approaches in skin disease detection using DL methodologies. The paper begins with an overview of the fundamental concepts of skin disease detection and the evolution of DL for this purpose. A critical component of this review is the comparative analysis between traditional and DL approaches for skin disease detection. The strengths and limitations of each approach are thoroughly examined, highlighting the superiority of DL in capturing complex patterns and improving diagnostic accuracy. The paper delves into the benchmark datasets commonly used for skin disease detection. Pre-processing techniques are discussed to enhance the quality of input data. Segmentation and its methods are explored to isolate skin lesions from the background. Feature extraction is a crucial step, and the paper presents various approaches to extract meaningful information from skin disease images. Various DL models are analysed for their effectiveness in skin disease detection and to provide insights into their implementation. Moreover, the review paper addresses the intense challenges faced in skin disease detection using DL, including limited and imbalanced data, high intra-class variability, and interpretability issues. Solutions such as data augmentation, transfer learning, ensemble learning, and attention mechanisms are proposed to address these challenges. In conclusion, this review paper provides a comprehensive overview of skin disease detection using DL methodologies. It consolidates the latest research and developments in the field.

Keywords— *Skin Disease, Features, Deep Learning, Segmentation, Challenges, Dermoscopic Images*

Introduction

The skin is the body's biggest organ; thus it naturally serves an important defensive function [1]. Its principal role is to protect the body from potentially hazardous environmental factors and to stop the loss of vital nutrients. However, many aspects of human life—including sun exposure, drinking, smoking, physical activity, infections, and the workplace—can negatively affect skin health. These elements not only cause harm to the skin but also pose risks to human health and, in extreme situations, even human life. Consequently, skin diseases have become prevalent among people of all cultural backgrounds and age groups [2].

A significant portion of the population, ranging from 30% to 70%, falls into high-risk groups for skin diseases. According to a 2018 study by the British Skin Foundation [3], over 60% of the British population experiences some form of skin illness. One in five Americans may develop cutaneous malignancy in their lives and there are around 5.4 million new instances of skin cancer documented annually in the United States. The impact of skin diseases on individuals is substantial, affecting daily activities, interpersonal relationships, and even internal organ functions [4]. Diseases of the skin can cause mental illness and, in the worst circumstances, terrible outcomes like despair and suicide. This has made the study of skin diseases a hot topic in contemporary medicine.

Figure 1 shows a worldwide search trend chart for skin diseases, which indicates the rising incidence of skin diseases around the world. Since 2011, there has been a steady increase in global searches for skin disease, reaching its peak by the year 2020. This reflects the growing awareness and concern about skin diseases among people globally. As such, addressing and understanding skin diseases have become critical areas of focus in the medical community.

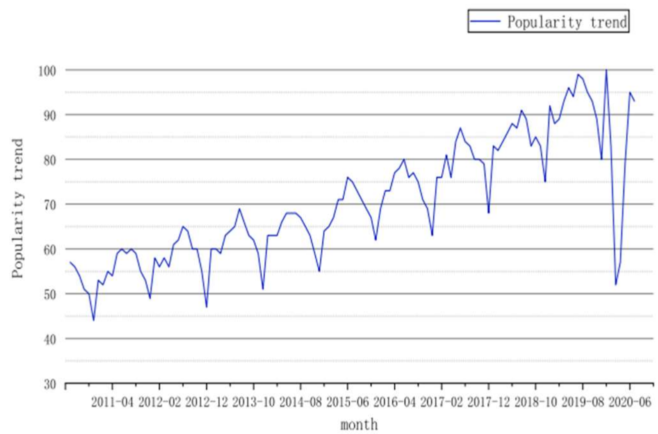

Fig 1. Global Skin Disease Thermal Map [5].

Early identification is critical in skin disease treatment for attaining a successful cure, reducing its impact, and increasing survival rates [6]. Early detection and treatment of skin illnesses can considerably reduce the harm. Skin disease recognition, on the other hand, is difficult due to the similarities of different skin disorders and a shortage of dermatologists with specific competence. As a result, effectively detecting skin diseases has emerged as a critical scientific challenge.

To tackle the intricacies of skin disease diagnosis and treatment, computer-aided diagnosis based on skin disease images has been utilized for automated recognition [7, 8]. The rapid progress in artificial intelligence, especially DL, has revolutionized computer vision. Particularly, the medical image processing of skin diseases has attracted significant interest, merging image processing, machine science, and intelligent medicine. Many experts and scholars are actively engaged in developing image recognition techniques to improve the precision of skin disease identification. This integration of DL and medical image processing holds significant promise in revolutionizing skin disease diagnosis and treatment, fostering improved patient outcomes.

Traditional Versus Deep Learning Method

The traditional medical diagnosis of skin diseases relies on doctors' expertise and the examination of dermatoscopic images to assess the condition of the skin. The diagnostic procedure involves visual observation by the doctor to gather relevant information, followed by histopathological and dermoscopy examinations. Dermoscopy is a non-invasive skin imaging technique that offers detailed visualization of the skin's structure at the interface between the superficial dermis and lower epidermis [9]. Dermatologists use various detection methods, such as the seven-point checklist, chaos and Clues [10], ABCD rule [11], cash (colour, architecture, symmetry, and homogeneity) [12], and three-point checklists [13], to analyse characteristics like nature, distribution, colour, edge contour, and shape of pigmented skin lesions. However, accurately identifying the pathological features of pigmented skin diseases can be challenging due to the similarities in colour, texture, and edge contour among different skin lesions and variations in pathological tissues among patients. Inadequate medical care is provided to patients because of their dependence on seasoned dermatologists for diagnosis. The entire process, from sample collection to medical diagnosis to histological analysis to patient report, might take up to five days, delaying therapy [14].

The development of DL has allowed us to overcome hurdles in skin disease diagnosis and image recognition that had previously been insurmountable [15]. Medical imaging of skin diseases, mathematical modelling, and computing power all come together in DL-based image identification, making it a truly multidisciplinary field [16]. To accomplish skin disease identification and treatment, it employs feature engineering and DL categorization methods. The capacity of DL to automatically discover deep-seated nonlinear correlations in medical images without the need for manual feature engineering, as is required by standard image recognition algorithms, has shown encouraging results in image identification. DL's adaptability and ease of transformation make it highly suitable for various fields and applications, including skin disease recognition and diagnosis. By leveraging DL technology, the skin disease diagnostic process can be expedited, leading to more efficient and accurate diagnoses, ultimately benefiting patients' treatment outcomes.

In Chapter 1, we explore skin disease detection and its association with DL. Chapter 2 provides a comparison between traditional and DL approaches for skin disease detection. Chapter 3 discusses the recent works in the area of skin disease detection. Chapter 4 outlines the methodology of skin disease detection using DL. Chapter 5 addresses the challenges faced and their solutions. Finally, Chapter 6 concludes the survey paper, summarizing key findings and highlighting the importance of continuous research and collaboration to enhance diagnostic accuracy in skin disease detection.

The objective of this research survey encompasses the following:

- To review and discuss recent research works and advancements in the field of skin disease detection using DL methodologies.
- To provide a comparative analysis between DL-based methods and traditional approaches for skin disease detection. By doing so, it intends to highlight the advantages and limitations of DL in terms of accuracy, efficiency, and complexity.
- To recognize and underscore challenges in skin disease detection using DL, while also proposing practical solutions to overcome these hurdles.
- To provide practical insights and recommendations for researchers, practitioners, and policymakers in the field of skin disease detection.

Related Works

The literature survey provides an in-depth exploration of recent advancements in the field of skin disease detection through the utilization of DL techniques. The following studies encompass a range of innovative methodologies and strategies for enhancing accuracy and efficiency in diagnosing various skin conditions. In the study [17], a groundbreaking DL-based model is introduced for predicting skin diseases. The study begins by employing Machine Learning (ML) algorithms to categorize skin disease classes using ensemble methods. Furthermore, a feature selection technique is applied to compare the resulting findings. A significant contribution is the creation of a web-based framework, built using Python Django, which aids specialists in identifying disease types. The study uniquely combines Support Vector Machine (SVM), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN) classifiers to enhance accuracy. Notably, the proposed model achieves a remarkable 95% accuracy rate, surpassing previous methods in diagnosing diverse skin conditions. The research [18] presents an approach for identifying and classifying bacterial and fungal skin diseases without dermoscopic images. The study focuses on five distinct classes, including two bacterial and two fungal disease categories, with healthy skin images as a fifth class. Leveraging the power of CNNs, the authors incorporate transfer learning via the fine-tuned VGG16 architecture. The introduction of a Streamlit-based web application enhances user interaction by displaying predicted skin disease results. Notably, this approach achieves an accuracy of 86% and an F1-score of 85%.

In the study [19], the emphasis is on the classification of prevalent fungal skin diseases using CNNs. A dataset comprising 407 fungal skin lesions is extensively pre-processed, encompassing image normalization, RGB-to-grayscale conversion, and image intensity balancing, followed by data augmentation. The resulting model demonstrates impressive accuracy, achieving a 93.3% classification rate for four common fungal skin diseases. Comparative analyses highlight the model's superiority over similar CNN architectures like MobileNetV2 and ResNet 50. The research [20] introduces an automated diagnostic system for identifying five common skin diseases. This innovative approach integrates clinical images and patient data collected via smartphone cameras. DL, specifically the pre-trained MobileNet-V2 model, is harnessed to create a multiclass classification model. Various data preprocessing and augmentation techniques enhance model performance, resulting in a remarkable accuracy rate of 97.5%, coupled with high sensitivity and precision levels of 97.7%. The objective of the study [21] revolves around the classification, detection, and accurate profiling of various skin diseases. To address this crucial issue, the researchers put forth a robust strategy involving a high-performance CNN. The methodology unfolds in a multi-fold manner, beginning with the preprocessing of skin disease images using specialized techniques. Subsequently, pivotal features from these images are extracted. The pre-processed images then undergo a comprehensive analysis through a Deep CNN. This approach is characterized by its simplicity, speed, and remarkable efficacy, yielding impressive results reaching up to a 98% accuracy rate.

The research [22] focuses on efficient skin disease recognition using CNN architectures. MobileNet and Xception CNN models, pre-trained on ImageNet, are employed for constructing an expert system. A transfer learning approach enhances feature discovery. Extensive evaluation of CNN architectures like ResNet50, InceptionV3, Inception-ResNet, and DenseNet confirms the effectiveness. The integration of transfer learning and augmentation boosts MobileNet's accuracy to 96.00%, and Xception achieves a remarkable 97.00%. A web-based architecture is introduced for real-time disease recognition. The author [23] introduces an advanced method for skin cancer detection that merges features from diverse sources. The process begins by refining images using a Gaussian Filter (GF) to reduce noise. Features are then extracted using both manual techniques like Local Binary Patterns (LBP) and automatic methods involving the Inception V3 model. The combination of traditional ML and modern DL techniques results in a potent system. An essential highlight is the Long Short-Term Memory (LSTM) network, which integrates extracted features to classify benign and malignant cases. The methodology is rigorously tested on the DermIS dataset, achieving an impressive accuracy of 99.4%, precision of 98.7%, recall of 98.66%, and a remarkable F-score of 98%. The article [24] presents a novel approach to identifying three specific skin diseases: Melanoma, Nevus, and Atypical. The process involves adaptive filtering to eliminate noise, followed by adaptive region growing to extract Regions of Interest (ROIs). A hybrid feature extraction method combining 2D-DWT, geometric attributes, and texture features enhances prediction accuracy. CNNs drive disease prediction, attaining a notable classification accuracy of 96.768% using the International Skin Imaging Collaboration (ISIC) dataset. The comprehensive strategy, encompassing preprocessing, segmentation, feature extraction, and CNN-based prediction, underscores its effectiveness. The research [25] pioneers unified DL-based segmentation of wrinkles and pores. The U-Net architecture, equipped with an encoder-decoder structure, captures intricate morphological skin structures. Attention mechanisms refine the focus on critical areas, improving segmentation precision. Positional information enhancement further aids in understanding the relative locations of skin features. A unique ground truth generation scheme is employed, tailored to each feature's resolution. The method achieves remarkable localization of wrinkles and pores, showcasing its potential for accurate skin analysis.

Methodology

In this chapter, we delve into the methodology used for skin disease detection using DL. We present a comprehensive block diagram, as depicted in Figure 2, to illustrate the various stages and components involved in the process. The block diagram serves as a visual representation of the steps and techniques employed to achieve effective skin disease detection through DL methods.

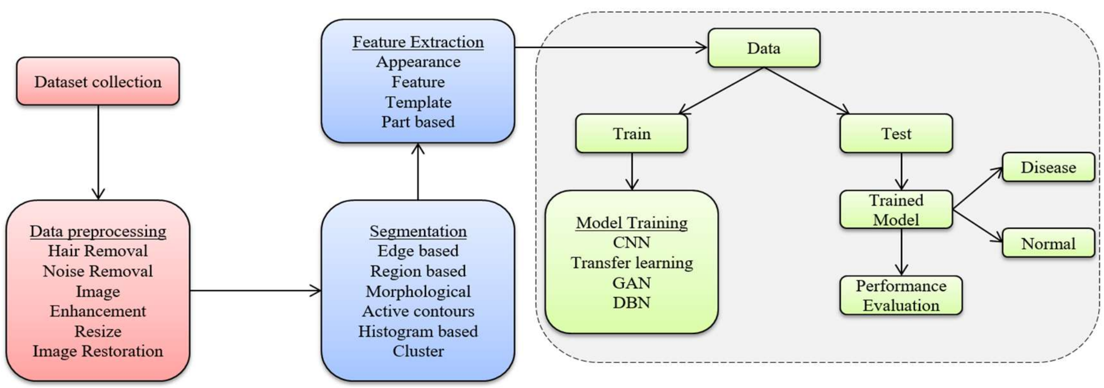

Fig. 2. Block Diagram of skin disease detectionData Collection:

Data acquisition for skin disease detection using DL involves two main approaches: direct data acquisition and benchmark datasets. Direct data acquisition includes collecting skin disease images from medical institutions and clinics and collaborating with dermatologists for labelled images. This customizes the dataset based on specific research goals. On the other hand, benchmark datasets are pre-existing collections of labelled skin disease images. Figure 3 displays sample images of various skin diseases extracted from the HAM10000 dataset. Some of the benchmark datasets for skin disease detection are tabulated in Table 1.

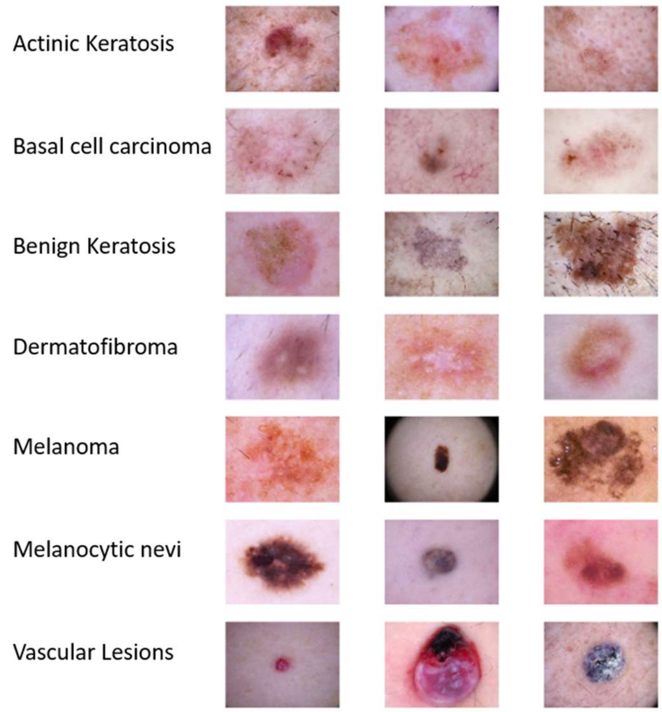

Fig. 3. Skin disease samples

Table 1. Skin disease dataset

Dataset	Image count	Classes
HAM10000 [26]	10,015	7
PH2Dataset [27]	200	3
ISIC 2016 [28]	1279	2
ISIC 2017 [28]	2600	3
ISIC 2018 [28]	11527	7
ISIC 2019 [28]	33569	8
ISIC 2020 [28]	44108	9
Dermofit [29]	1300	10
BCN20000 [30]	19424	8
PAD-UFES-20 [31]	2298	6

- HAM10000 (Human Against Machine with 10,000 training images): Contains 10,015 dermoscopic images of various skin lesions, including melanoma, nevi, and other benign and malignant conditions. Metadata is available for each image, including lesion type, clinical diagnosis, age of the patient, and sex. Created for a challenge where dermatologists and ML algorithms competed to diagnose skin lesions accurately. Widely used for research in skin disease classification, computer-aided diagnosis, and DL model development.

- PH2Dataset: Comprises 200 dermoscopic images primarily focused on pigmented skin lesions for melanoma research and diagnosis. Provides ground truth data, including lesion borders, colours, and texture analysis, valuable for algorithm development. Suitable for researchers developing computer-aided diagnosis systems for melanoma detection and differentiation from benign lesions. A valuable resource for studying the characteristics of pigmented lesions.

- ISIC Datasets (2016, 2017, 2018, 2019, 2020): Each year's dataset contains clinical images of various skin lesions obtained from different sources and years. Used for annual skin lesion classification challenges, encouraging participants to submit algorithms for evaluation. A benchmark for skin disease classification, advancing research and development in the field of dermatology. Enables comprehensive research and classification tasks due to its diverse range of skin conditions and a large number of images.

- Dermofit: Contains images of various skin conditions, such as eczema, psoriasis, and skin cancers. Supports the development and evaluation of algorithms for skin disease detection and classification. Useful for researchers exploring multiple skin diseases beyond melanoma and nevi. Aims to contribute to the improvement of skin disease diagnosis and management.

- BCN20000: Comprises 20,000 dermoscopic images focused on melanoma classification and computer-aided diagnosis. Created to support research in ML-based approaches for dermatology. Enables the evaluation of large-scale algorithms and methods for skin disease detection. Aims to advance the accuracy and efficiency of skin disease diagnosis through automated methods.

- PAD-UFES-20: Contains 20,000 dermoscopic images for various skin lesions, designed to support research in automated skin disease detection. A valuable resource for developing and evaluating computer-aided diagnosis systems in dermatology. Provides ample data for training and validating DL models and other ML approaches. Aims to improve the early detection and diagnosis of skin diseases for better patient outcomes.

Data Pre-processing:

Skin disease detection is a critical task in the medical field, particularly in dermatology and diagnostics. DL, a subset of artificial intelligence, has demonstrated remarkable success in various image recognition tasks, including skin disease detection. However, prior to feeding skin images into the DL model, several pre-processing steps are necessary to enhance data quality and eliminate unwanted artifacts that could impact the model's performance [32, 33]. This article explores the pre-processing steps involved in skin disease detection using DL, as well as the commonly employed algorithms for each step.

Hair Removal: Hair removal is essential to eliminate hair artifacts that may interfere with accurate skin lesion detection [34, 35]. Hair regions can overlap with lesion areas, leading to false positives and reduced model performance. Figure 4 shows the images of the dermoscopic image before and after the hair removal process. The key steps involved in hair removal are as follows:

- Hair Segmentation: Hair segmentation is the process of identifying hair regions in the skin images. DL-based approaches like U-Net, Mask R-CNN, or morphological operations can be employed for accurate hair segmentation.

- Hair Removal: Once the hair regions are identified, they are removed from the original skin image using techniques like mask-based removal or inpainting. Mask-based removal involves using the hair segmentation mask to mask out the corresponding pixels in the image. In inpainting, the hair regions are filled in with plausible information to remove the hair.

Fig. 4. Skin image before and after hair removal

Noise Removal: Skin images may be affected by various types of noise during acquisition or transmission, which can hinder the model's performance. Noise removal is crucial to improve data quality and enhance the model's robustness [36]. Common algorithms for noise removal include:

- Median Filtering technique replaces each pixel in an image with the median value of its neighbouring pixels [37]. It is effective in reducing impulse noise or salt-and-pepper noise.
- Gaussian filtering applies a Gaussian kernel to the image to reduce Gaussian noise. It is particularly useful for smoothing noise reduction.
- Denoising Autoencoders are DL models designed to reconstruct clean images from noisy inputs [38]. Training these autoencoders helps in learning noise patterns and removing noise during inference.

Image Enhancement: Image enhancement techniques are applied to improve the visibility of skin lesions and highlight important features [39]. These techniques aid the DL model in detecting subtle patterns and textures related to different skin diseases. Common enhancement methods include:

- Histogram Equalization technique redistributes pixel intensities to improve image contrast, making it easier to identify fine details in the skin images [40].
- Contrast Stretching expands the range of pixel intensities, spreading out the pixel values for better visualization [41].
- Adaptive Histogram Equalization method enhances local contrast in different regions of the image, revealing fine details and texture variations.

Resize: DL models typically require fixed-size inputs for efficient processing [42]. Therefore, resizing skin images to a standard size is crucial to ensure compatibility with the neural network architecture. Commonly, images are resized to a square or rectangular shape while preserving the aspect ratio. Libraries like OpenCV or PIL are commonly used for image resizing.

Image Restoration: Skin images may suffer from various degradations like blurring or compression artifacts. Image restoration techniques are used to recover the original quality of the images, ensuring that the

DL model receives high-quality inputs [43]. Common restoration methods include:

- Deblurring: Deblurring algorithms [44] aim to reduce blurriness caused by camera shake or other factors, leading to clearer images.
- JPEG Artifact Removal: When skin images are compressed using JPEG, compression artifacts can affect the model's performance. JPEG artifact removal techniques aim to reduce these artifacts and restore image quality.

Segmentation:

Segmentation is a critical image-processing task that involves dividing an image into distinct regions or objects of interest [45]. Figure 5 illustrates the skin image before and after segmentation.

Fig. 5. Skin image before and after segmentation

There are five main types of segmentation methods: Let's explore each of these methods and their subtypes in detail:

1. **Edge-based Segmentation:** Edge-based segmentation focuses on identifying boundaries or edges between different regions in an image. Edges represent abrupt changes in intensity, colour, or texture, and they are often indicative of object boundaries. Detecting edges is vital in applications where the shape or contour of objects is of primary interest.

Canny Edge Detection: The Canny edge detector is one of the most popular edge detection algorithms due to its effectiveness and robustness [46]. It involves several key steps:

1. Convert the input image into grayscale to simplify the edge detection process and reduce computational complexity.
2. Calculate the gradient magnitude and direction of the image. The gradient magnitude represents the rate of change of intensity at each pixel's location, helping identify regions with significant intensity changes that are likely to edge.
3. The gradient magnitude (G) at a pixel (x, y) can be computed using gradient operators like the Sobel operator: $G(x, y) = \sqrt{G_x(x, y)^2 + G_y(x, y)^2}$
4. G_x and G_y are the gradient components along the x and y axes, respectively. They can be obtained by convolving the image with the Sobel filters.

5. Suppress non-maximum gradient values to obtain thin and accurate edges. For each pixel (x, y) with a gradient magnitude $G(x, y)$, compare it with the gradient magnitudes of its two neighboring pixels in the gradient direction (θ). Retain the pixel only if it has the maximum gradient value compared to its neighbors.
6. Apply double thresholding to classify the edges as strong, weak, or non-edges. Set two thresholds: a high threshold (T_{high}) and a low threshold (T_{low}). Pixels with gradient magnitudes greater than T_high are considered strong edges, and those between (T_{low}) and (T_{high}) are considered weak edges. Pixels with gradient magnitudes below (T_{low}) are treated as non-edges and discarded.
7. Perform edge tracking to link weak edges to strong edges and form continuous edge paths. Starting from a strong edge pixel, trace the connected weak edges that are 8-connected (i.e., sharing a common vertex or edge).

Sobel Edge Detection: Sobel edge detection is another well-known edge detection method, often used as a simpler alternative to the Canny edge detector [47]. The Sobel operator is a convolutional kernel used to compute the gradient magnitude [48], similar to the Canny edge detection's Step 2. The Sobel operator has two kernels, one for the x-direction and another for the y-direction. The convolution of the image with these kernels yields the gradient components G_x and G_y, which can be used to compute the gradient magnitude as mentioned earlier.

2. Region-based Segmentation: Region-based segmentation groups pixels into coherent regions based on their similarity in colour, intensity, texture, or other feature spaces. This approach aims to group pixels that are likely to belong to the same object or region, irrespective of the presence of edges.

Region-growing: This is a straightforward region-based segmentation technique that starts from seed points and iteratively expands the regions by adding neighbouring pixels that satisfy certain similarity criteria [49]. The similarity criterion could be based on colour, intensity, texture, or other feature spaces.

Let R_i represent a region, and p_{ij} is the pixel at position (i, j) in the image. The similarity criterion for adding a neighboring pixel p_{xy} to region R_i can be defined as: similarity $\left(R_i, p_{xy}\right) = \left|F\left(p_{xy}\right) - F\left(p_{ij}\right)\right| \leq T$

Where F is a feature function that measures the similarity between pixels, and T is a predefined threshold that determines the allowable difference in feature values.

The region-growing process can be initialized with one or more seed pixels. Pixels that are similar to the seed pixels are added to the region, and this process is iteratively repeated until no more pixels can be added.

Watershed Segmentation: The watershed segmentation algorithm is inspired by the topographic concept of a watershed, wherein an image's intensity landscape is analogized to a topographic relief [50]. The image's intensity values are treated as height values, and the watersheds correspond to regions where water would accumulate if the intensity landscape were flooded. The process of watershed segmentation begins by transforming the image's intensity values into a gradient image, which effectively highlights the boundaries between different regions. Next, local minima are identified in the gradient image, and these minima serve as markers for the subsequent segmentation process. The algorithm then initiates a flooding procedure, starting from these markers and progressively dividing the image into distinct regions based on the local intensity minima. The watershed lines are consequently formed, demarcating the boundaries between these segmented regions.

3. Morphological Segmentation: Morphological operations process images based on the shape and structure of objects within the image [51]. The mathematical formulas for the fundamental morphological operations are as follows:

- Dilation: Dilate a binary image A by a structuring element B, resulting in a new image C, defined as $C = A \oplus B$. The dilation operation expands the regions in the image.
- Erosion: Erode a binary image A by a structuring element B, resulting in a new image C, defined as $C = A \ominus B$. The erosion operation shrinks the regions in the image.
- Opening: Perform erosion followed by dilation ($C = A \ominus B \oplus B$) to remove noise and small objects.
- Closing: Perform dilation followed by erosion ($C = A \oplus B \ominus B$) to close small gaps in the regions.

4. Active Contours: Active contour models, also known as snakes, are used to locate the boundaries of objects in an image by minimizing an energy function [52]. The mathematical representation of snakes is as follows:

$$E = \int \left[\propto (s) \left| \frac{\partial s(s)}{\partial s} \right|^2 + \beta(s) \left| \frac{\partial^2 s(s)}{\partial s^2} \right|^2 \right] ds - \int \delta(I(s) - IO)^2 \, ds$$

Here, s represents the curve parameterized by arc length, $\frac{\partial s(s)}{\partial s}$ is the tangent vector to the curve, $\frac{\partial^2 s(s)}{\partial s^2}$ is the curvature of the curve, $I(s)$ is the image intensity at point s along the curve, and IO is the desired intensity value for the contour. α and β control the internal elasticity and smoothness of the contour, respectively, and δ is a weighting factor for the image term.

4. Histogram-based Segmentation: Histogram-based segmentation involves analysing the pixel intensity distribution in an image [53]. Thresholding is a common technique. Let $H(I)$ represent the histogram of an input grayscale image I. The thresholding process can be defined as:

- Choose a suitable threshold T to separate the pixels into two classes: foreground and background.
- Binary Segmentation assign each pixel in the image I to either the foreground or background class based on the threshold T:

$$Binary\ Image\ (x, y) = \begin{Bmatrix} 1 & if\ I(x, y) > T \\ 0 & Otherwise \end{Bmatrix}$$

5. Clustering-based Segmentation: Clustering techniques, such as k-means clustering or Gaussian mixture models, offer valuable tools for grouping pixels into clusters based on their feature similarity [54]. When applied to skin disease detection, clustering can effectively identify regions with distinct color or texture properties, potentially corresponding to lesions or affected areas.

K-means Clustering: The k-means algorithm achieves pixel grouping by minimizing the sum of squared distances between each pixel and its assigned cluster centroid [55]. The process can be summarized as follows:

i. Randomly initialize k cluster centroids.
ii. Assign each pixel to the nearest cluster centroid based on the Euclidean distance.
iii. Recalculate the cluster centroids based on the newly assigned pixels.
iv. Repeat steps ii and iii until convergence or a maximum number of iterations.

Gaussian Mixture Models (GMM): GMM operates on the assumption that pixels in an image belong to multiple Gaussian distributions, each representing a different region [56]. The algorithm estimates the parameters (mean and covariance) of these Gaussian distributions and assigns pixels to the clusters probabilistically.

i. Initialize the parameters (mean and covariance) of the Gaussian distributions randomly.
ii. Assign each pixel to the Gaussian distribution that maximizes the posterior probability (using the Expectation-Maximization algorithm).
iii. Update the parameters of the Gaussian distributions based on the newly assigned pixels.
iv. Repeat steps ii and iii until convergence or a maximum number of iterations

Feature Extraction

Feature extraction plays a vital role in skin disease detection using DL, as it involves converting raw image data into meaningful representations that capture relevant information about the skin lesions or affected areas [57]. Several feature extraction methods are employed, including appearance-based, feature-based, template-based, and part-based approaches. Let's explore each of these methods in detail:

1. Appearance-based Feature Extraction: This method focuses on capturing the visual appearance of skin lesions in the image. It extracts low-level image features like colour, texture, and shape to represent the lesions [58]. DL models, particularly CNNs, are commonly used for this purpose due to their ability to automatically learn hierarchical features from raw image data. Colour is a critical visual cue in skin disease detection, and colour-based feature extraction methods involve quantifying the colour distribution in the image [59]. This can be achieved using colour histograms or colour moments, such as mean and standard deviation, to represent the colour information of the skin lesions. Texture features, on the other hand, capture patterns and variations in pixel intensities within the skin lesions. Texture-based feature extraction methods [60] employ filters like Gabor filters or Local Binary Patterns (LBP) to extract texture information from the image, characterizing the texture properties indicative of certain skin diseases. Shape features describe the geometric properties of skin lesions, such as size, symmetry, and contour. These features are extracted by analysing the boundary or contour of the lesions, with common methods including Fourier descriptors, Hu moments, and Zernike moments.

2. Feature-based Feature Extraction: The predefined feature descriptors are used to represent skin lesions in the image, capturing specific characteristics such as texture, edges, or keypoints. SIFT (Scale-Invariant Feature Transform) is a popular method that identifies keypoints in an image and computes descriptors based on local image gradients [61]. Its scale and rotation invariance makes it suitable for detecting and matching keypoints in images with different scales and orientations. HOG (Histogram of Oriented Gradients) is commonly used for object detection tasks, including skin disease detection. It computes the distribution of gradient orientations in the image, capturing local shape and edge information, particularly useful for detecting irregularly shaped skin lesions.

3. Template-based Feature Extraction: This method employs a predefined template or reference image [62] of a specific skin disease to detect similar lesions in the input image. Template matching is a simple and intuitive method where a template image of a known skin disease is compared to patches of the input image. The template is slid across the image, and similarity measures like correlation coefficients or the sum of squared differences are computed at each location to find the best match.

4. Part-based Feature Extraction: This approach focuses on capturing local parts or regions of interest [63] within the skin lesions, aiming to extract discriminative parts contributing to the overall disease diagnosis. Spatial Pyramid Matching (SPM) is a method that divides the image into multiple levels of grids and extracts features from each grid level [64]. The extracted features are then concatenated to form a hierarchical representation of the image, capturing both global and local information suitable for skin disease detection tasks. In DL-based skin disease detection, appearance-based feature extraction using CNNs is the most common approach. CNNs automatically learn hierarchical features from raw image data, allowing them to capture complex patterns and structures in skin lesions. Transfer learning, where pre-trained CNN models on large datasets are fine-tuned for skin disease detection, is also widely used to boost performance with limited data.

Deep Learning

The detection of skin diseases poses a significant challenge in medical image analysis, and DL models have emerged as a promising solution in revolutionizing this field. Among various DL architectures, CNNs have shown exceptional potential for skin disease detection [65]. CNNs are tailored for image-related tasks, proficiently learning hierarchical features from raw image data. Using convolutional layers, they extract local patterns S features, pooling layers reduce spatial dimensions, and fully connected layers make final predictions. In skin disease detection, CNNs adeptly capture visual characteristics of lesions, such as colour, texture, and shape, facilitating accurate classification of diverse skin conditions.

However, a common challenge in medical image analysis, including skin disease detection, is the scarcity of labelled data. Here, Transfer Learning comes to the rescue [66]. This powerful technique involves using a pre-trained CNN model, such as one trained on a large dataset like ImageNet, as a starting point. The pre-trained CNN model is then fine-tuned on the target dataset of skin disease images, adapting to the specific detection task. Leveraging knowledge learned from a large dataset enhances performance on the skin disease detection task, even with smaller datasets.

Generative Adversarial Networks (GANs) offer unique capabilities in skin disease detection. Comprising a generator and discriminator, GANs primarily excel in image synthesis tasks [67]. For skin disease detection, GANs generate realistic synthetic images for data augmentation, crucial in training DL models with limited datasets. Synthetic images that resemble real images enrich the training dataset and enhance the model's generalization ability. GANs can also be used for anomaly detection in skin disease images, identifying deviations or abnormalities in skin images for early detection of abnormal lesions.

Deep Belief Networks (DBNs), although less commonly used in skin disease detection compared to CNNs and Transfer Learning, play essential roles in unsupervised feature learning and dimensionality reduction. In unsupervised feature learning, DBNs automatically learn informative features from raw image data without explicit annotations [68]. These features can then train classifiers for skin disease detection. Additionally, DBNs are employed in dimensionality reduction, reducing computational complexity and memory requirements of DL models. As DL research progresses, these models are expected to play an increasingly vital role in the early and accurate diagnosis of skin diseases, ultimately leading to improved patient outcomes and enhanced healthcare practices.

Challenges and Possible Solutions

The significant challenges encountered in skin disease detection through DL are discussed below. The formidable obstacles are illustrated in Figure 6.

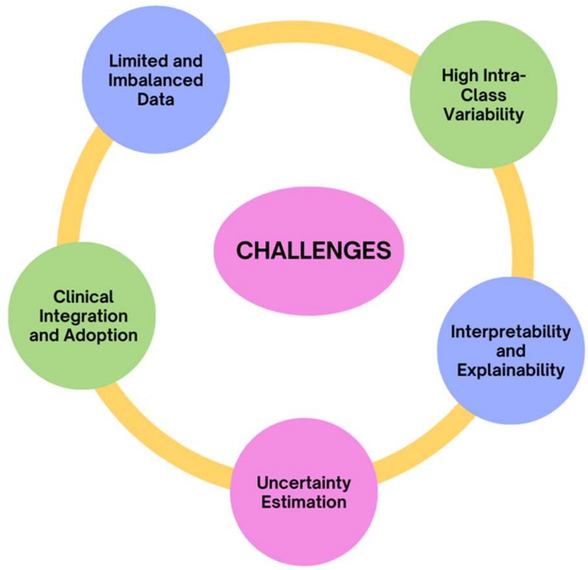

Fig. 6. Challenges faced in skin disease detection using DL

1. Limited and Imbalanced Data: Obtaining a vast and diverse dataset of labelled skin disease images is a formidable task, and the dataset may suffer from class imbalance, where some skin conditions have significantly fewer samples than others [69]. Solution: Employing data augmentation techniques to generate synthetic images and balance the class distribution can be a viable approach. Techniques like rotation, flipping, and zooming can introduce variations in existing images, thereby increasing the dataset size. Additionally, transfer learning can be harnessed to leverage pre-trained models on larger datasets and fine-tune them on the skin disease dataset, even when faced with limited samples.

2. High Intra-Class Variability: Skin diseases often display diverse visual characteristics and may manifest differently among patients, posing challenges in accurately distinguishing between subtypes of the same condition [70]. Solution: Implementing ensemble learning can be beneficial, where multiple models specializing in detecting specific subtypes or manifestations of skin diseases are combined. By aggregating the predictions of multiple models, the overall diagnostic performance can be improved, capitalizing on the diversity in model predictions.

3. Interpretability: DL models are often perceived as "black boxes," making it difficult to comprehend and interpret their decisions, a critical aspect in medical applications [71]. Solution: Incorporating attention mechanisms in DL models can highlight regions of the image that significantly influence the diagnosis. Moreover, utilizing explainable AI techniques like LIME (Local Interpretable Model-Agnostic Explanations) can provide post-hoc explanations of the model's predictions, enabling dermatologists to understand the rationale behind the model's decisions.

4. Uncertainty Estimation: DL models frequently provide deterministic predictions without quantifying the uncertainty associated with their decisions [72]. In medical applications, understanding the model's uncertainty is vital to evaluate the reliability of the diagnosis. Solution: Leveraging Bayesian DL techniques

can estimate the uncertainty in model predictions. These methods offer probabilistic outputs, facilitating the quantification of uncertainty and enhancing the model's robustness in decision-making.

5. Clinical Integration and Adoption: Integrating DL models into clinical workflows and gaining acceptance from dermatologists and healthcare professionals can be challenging due to concerns about relying solely on AI-driven diagnoses. Solution: Collaborating closely with dermatologists and involving them in the development and validation of the models can still in trust and acceptance. Providing clear and interpretable model outputs, along with explanations, can further boost confidence in the model's predictions. Conducting prospective clinical studies and trials to demonstrate the efficacy and safety of the DL model in real-world settings can foster its adoption in clinical practice.

Conclusion

This review presents a comprehensive overview of the advancements in skin disease diagnosis using DL. The paper discusses a step-by-step procedure for automating skin disease detection with DL. It begins by introducing publicly available skin image datasets, followed by a brief introduction to pre-processing techniques. Next, segmentation methods and their types are explored, and detailed feature extraction techniques are discussed. The conception and popular architectures of DL, along with commonly used frameworks, are introduced. The review also delves into the challenges that remain in the field of skin disease diagnosis with DL and proposes future research directions.

Compared to existing literature reviews, this article provides a systematic survey of recent applications of DL in skin disease diagnosis. It offers readers an intuitive understanding of essential concepts and the challenges faced in this area. The review also highlights possible directions for addressing these challenges, which will benefit those interested in further research. The potential benefits of automated skin disease diagnosis with DL are significant. However, the accuracy and reliability of such systems must be critically tested before implementation in real-life clinical settings. While many DL systems have shown promising results on experimental skin disease datasets, thorough validation and testing are crucial for acceptance in clinical diagnosis tasks.

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