DETECTION OF SKIN DISEASES FROM IMAGES USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

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Today, classification of skin diseases based on automated systems by analyzing medical images taken from the affected skin surface is one of the important methods to be studied. Skin diseases are one of the global health problems that is increasing year by year and endangering the lives of many people. Early detection of this disease is crucial in preventing its progression and its consequences. Currently, many studies are being conducted to detect skin diseases at early stages and several solutions are being proposed. In particular, classification of skin diseases based on medical images using intelligent systems is one of the best solutions proposed by researchers. In this research work, the methods, models and algorithms for automatic classification of skin diseases based on computer-aided machine learning (ML) and deep learning (DL) algorithms were analyzed. Also, methods for pre-processing medical images were studied to ensure fast and accurate performance of ML and DL models. As a result of the analysis, comparative tables were developed for further research work to compare the results of previous studies and the accuracy of the models proposed in them. The main goal of the study is to fill the research gap in the application of ML and DL models in skin disease classification. This study will help researchers find better solutions for classifying skin diseases, identify existing problems and recent achievements in the classification.

Key words: Skin diseases, Medical images, Image preprocessing, Segmentation, Classification, Machine learning, Deep learning.

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ВЫЯВЛЕНИЕ КОЖНЫХ ЗАБОЛЕВАНИЙ ПО ИЗОБРАЖЕНИЯМ С ИСПОЛЬЗОВАНИЕМ МЕТОДОВ МАШИННОГО ОБУЧЕНИЯ И ГЛУБОКОГО ОБУЧЕНИЯ

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В настоящее время одним из важнейших методов, требующих изучения, является классификация кожных заболеваний на основе автоматизированных систем, работающих с медицинскими изображениями, полученными с поверхности пораженной кожи. Кожные заболевания представляют собой глобальную проблему здравоохранения: их распространенность ежегодно увеличивается, создавая серьезную угрозу жизни и здоровью миллионов людей. Ранняя диагностика играет ключевую роль в предотвращении прогрессирования болезни и ее осложнений. Сегодня ведется большое количество исследований, направленных на выявление кожных заболеваний на начальных стадиях, и предлагаются различные решения. Одним из наиболее перспективных подходов, предложенных учеными, является использование интеллектуальных систем для классификации заболеваний по медицинским изображениям. В данной работе были проанализированы методы, модели и алгоритмы автоматической классификации кожных заболеваний на основе машинного обучения (ML) и глубокого обучения (DL). Также были изучены методы предварительной обработки медицинских изображений, позволяющие повысить точность и скорость работы моделей. В ходе анализа сопоставлены результаты предыдущих исследований и оценена точность предложенных в них моделей, а также подготовлены сравнительные таблицы для использования в будущих научных работах. Цель исследования — восполнить существующий пробел в области применения ML и DL для классификации кожных заболеваний. Полученные выводы помогут исследователям разрабатывать более эффективные решения, выявлять текущие проблемы и учитывать новейшие достижения в данной сфере.

Ключевые слова: кожные заболевания, медицинские изображения, предварительная обработка изображений, сегментация, классификация, машинное обучение, глубокое обучение.

Introduction. Worldwide, skin diseases account for 1.79 % of the global burden of all other types of disease. According to the American Academy of Dermatology, 1 in 4 people in the United States have a skin disease [1]. The most common and dangerous types of skin diseases are eczema, melanoma, psoriasis, squamous cell carcinoma, basal cell carcinoma, etc. [2]. Today, modern intelligent systems have emerged as a promising approach to develop automated and objective computer-based classification models for skin diseases. Accurate classification of skin diseases using automated systems is a very important task. Because it directly affects human life. Therefore, even a small uncertainty can put the lives of patients at risk. Therefore, over the past few decades, researchers have been working on developing methods to automatically

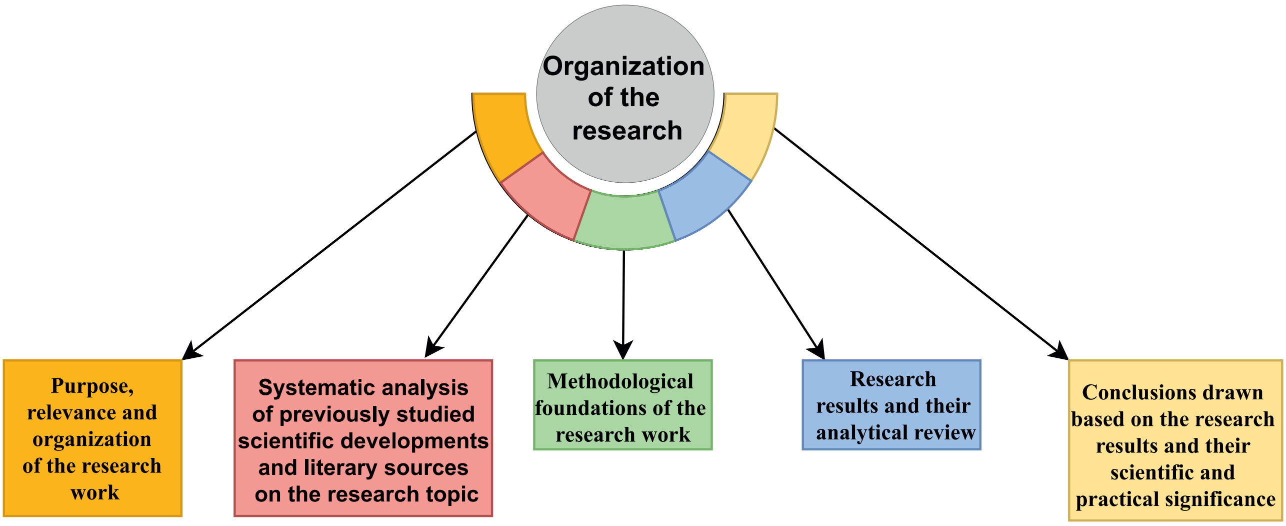

Fig. 1. Research organization diagram

diagnose various forms of skin diseases by applying machine learning and deep learning methods and improving their accuracy.

The purpose of this study is to review ML and DL methods that can be used for computer-aided diagnosis of skin diseases, as well as to analyze previous and current studies on the classification of skin diseases. The relevance of the research work is to analyze the methods of correctly selecting artificial intelligence models and adjusting their parameters in the classification of skin diseases, as well as the application of pre-processing techniques to medical images. Since these methods are used to perform initial assessments of the most suspicious skin lesions. The study analyzed the quality of evidence, the usefulness of algorithms, the different types of skin diseases for which artificial intelligence is used, the impact on primary care, and the possibilities of using computers.

The main focus of intelligent systems for detecting skin diseases using skin surface images is to extract the characteristics of these diseases. Knowing the specific characteristics of each disease and its location on the skin surface is a key step in classifying the disease. Table 1 below lists some common skin diseases and their characteristics.

Analyzing skin diseases based on medical images, it is necessary to extract the specific features of skin diseases. Dermatological diseases, unlike internal diseases, usually manifest externally, therefore, a deep understanding of visual signs and subtle differences in skin texture, color, and pattern is required [10]. Capturing and analyzing these complex visual features is essential to ensure accurate and reliable classification of skin diseases. By applying medical image processing technologies based on ML and DL algorithms, scientists are developing approaches to diagnose skin lesions with complex features. These approaches are expected to lead to better classification of skin diseases, more accurate diagnosis of patients, and more effective global health care [11]. The organization of this research work is as follows (Figure 1): Section 2 presents a literature review; Section 3 discusses the general methodology of ML and DL approaches in skin disease diagnosis; Section 4 presents the research results; and Section 5 presents the research conclusions.

I. Literature review. Today, ML and DL have emerged as promising approaches to develop automated and objective classification models for skin diseases using computers. The

Table 1

Common skin diseases and their characteristics

N	Skin disease appearance	Type of disease	Characteristics	Location on the body
1.		Eczema	It is the most common chronic inflammatory skin disease, affecting 15–30 % of children and 2–10 % of adults worldwide [3]. In people with fair skin, eczema rashes may appear pink, red, or purple. If the skin is darker, the eczema rash may be purple, brown, or gray.	Eczema is most common on the elbows, backs of the knees, neck, and face.
2.		Psoriasis	It is a common chronic immune-mediated inflammatory skin disease, affecting approximately 2–3 % of the general population worldwide [4]. The disease presents as a silvery, red, scaly rash.	It can involve the palms and soles of the human body, the scalp, and the nails. The disease most often manifests itself in a sharply demarcated appearance on the flexural surfaces of the elbows and knees and in the lumbar region [5].
3.		Lupus Erythematosus	The incidence of lupus is 241 per 100,000 adults in the United States and 210 per 100,000 in Spain [6, 7].	Any part of the body
4.		Basal Cell Carcinoma (BCC)	Basal cell carcinoma (BCC) can appear on the skin as a flesh-colored, pearly lump or a pinkish spot. It often appears as a shiny, pearly, or clear bump or nodule that is pink, red, or white [8].	It is usually found on the skin of the face, neck, and ear areas.
5.		Squamous Cell Carcinoma (SCC)	A hard bump on the skin called a nodule. The nodule may be the same color as the skin or may look different. Depending on the skin color, it may appear as a flat sore with a crust that is pink, red, black, or brown [9].	It is usually found on the skin of the face, neck, and ear areas.
6.		Melanoma	It often develops within the skin or may appear suddenly as a new, dark spot on the skin. The spot is asymmetrical, meaning that the two sides do not match, and the borders of the spot may be uneven or defined. The spot may be of several colors, including brown, black, red, blue, or white [9].	Among men, melanoma usually develops on the upper body, especially the upper back, while among women, melanoma most often appears on the legs.

high accuracy of ML and DL techniques in classifying skin diseases has led to their increased application. This section reviews the studies conducted by researchers in the field of diagnosing some common skin diseases using DL and ML models.

Several studies have proposed the use of ML algorithms for eczema detection. In particular, in the article "A method for automatic eczema disease classification using supervised learning" by researchers Nisar H., Ch'ng Y. K., Ho Y. K., supervised learning ML algorithms for eczema classification using Support Vector Machine (SVM), Naive Bayesian Classifier (NBC) and K-Nearest Neighbor (KNN) algorithms were presented [12]. The researchers initially performed image preprocessing methods on the acquired images to improve image quality and performed image segmentation. The features obtained from the training images were ranked using Fisher score, standard deviation, T-statistic score and correlation coefficient to extract the most important features. In this, the researchers used features such as color, size, intensity and texture to train the model. As a result of the classification, the SVM classifier shows the best segmentation result with an accuracy of 84.43 %, while the accuracy of NBC and KNN is 82.77 % and 83.53 %, respectively.

Researchers such as M. Jagdish, SP Gualan Guamangate, MAG Lopez, JA De La Cruz-Vargas, MER Camacho have conducted research on skin disease classification using ML algorithms [13]. They developed skin disease detection models using image processing techniques. To classify skin diseases, 50 image samples were taken from the skin surface and pre-processed using wavelet analysis. Using the pre-processed sample images for classification, they used fuzzy clustering methods with KNN and SVM ML algorithms. They achieved 91.2 % classification accuracy using the KNN classification algorithm. According to the results of the study, when the KNN algorithm was compared with the SVM technique, it was found that the KNN algorithm performed better. Scientists identified the types of skin diseases using these classification methods. However, they only used 50 sample images, which included basal and squamous cell carcinoma diseases.

Using images of skin surfaces affected by diseases such as melanoma, psoriasis, and acne, researchers S. A. AlDera, M. T. B. Othman presented a model for diagnosing skin diseases [14]. The researchers used a dataset of 377 images of 4 different disease classes in this work. During the pre-processing stage, the image samples obtained were resized to 250*250 and the median method was used to reduce noise in the images. Then, the color images were converted to a grayscale model for segmentation and extraction tasks and the Otsu method was used for segmentation. In this work, features were extracted using Entropy, Gabor, and Sobel methods to extract image texture features. Finally, after the features were extracted, a model was developed based on ML algorithms SVM, Random Forest (RF), and K-Nearest Neighbors (KNN) classifiers for disease classification. The results of the proposed model show that SVM achieved 90.7 % accuracy, while RF and KNN achieved 84.2 % and 67.1 %, respectively. As a result, the SVM classifier achieved better accuracy than other ML algorithms. The model proposed by the researchers can only achieve high accuracy when using a larger dataset of images.

Researcher Mustafa Qais Hatem developed an algorithm to classify skin diseases as dangerous or safe using their lesions [15]. He used a KNN algorithm to classify skin lesions according to their severity. The proposed system used dermoscopic images as a dataset. In the initial stage, morphological "closure" was used to improve image clarity, facilitate skin lesion segmentation, and filter the shape and structure of the image. Both traditional and adaptive thresholding methods were used to segment skin lesions. Then, segmented dermoscopic lesions were used to extract disease features. Lesion parameters were determined using mathematical formulas such as the mean value. The system proposed by the researcher achieved 98 % accuracy using a KNN classifier for only two classes (dangerous or safe).

Jonathan Souza, Tiago Mota de Oliveira, Claudemir Casa, and Andre Roberto Ortoncelli [16] researchers conducted a study on the early detection of lupus skin disease from images and proposed an automatic lupus detection approach. The study used 905 lupus images as an experimental database. In the preprocessing stage, all images in the database were resized to a standard size of 224x224 and new images were created to increase the data. This approach combines a clustering strategy and a Transfer Learning-based lupus detection method. The experiments were conducted with eight pretrained models of the CNN architecture, and the highest accuracy of 96 % was achieved with the Densenet-121 model. The main difficulty in this work is the lack of a large database of lupus images.

Researchers such as Samir Bandyopadhyay, Payal Bose, Amiya Bhaumik, Sandeep Poddar [17] developed a hybrid algorithm for detecting 9 different skin diseases based on experience. In this project, about 40 thousand skin surface images were collected from the ISIC repository to detect skin diseases. Pre-processing steps such as removing noise from the images, adjusting their brightness and contrast levels, and adjusting the sharpness level to enhance the edges of the dark level were performed on the images. To carry out this study, DL algorithms such as Googlenet, Resnet50, Alexnet, and VGG16 were used to extract lesion features from the skin surface, and Decision Tree (DT), Multi-Class Support Vector Machine, and AdaBoost Ensemble ML models were used as classification models. As a result of this study, the researchers proposed a hybrid model of ML and DL models. According to the proposed model, 4 DL models were combined with ML classifiers to extract features from the training data, and a full comparative analysis was conducted. As a result, it was found that the Resnet50 hybrid model with SVM gave the best results for classifying skin diseases with an accuracy rate of 99 %.

Researchers Laura K Ferris, Jean A Harkes, Benjamin Gilbert, Daniel G Winger, Ksenia Golubets, Oleg Akilov, Mahadev Satyanarayanan used the DT classifier in their article "Computer-aided classification of melanocytic lesions using dermoscopic images" in order to assess the severity of skin lesions using dermoscopic images and evaluated the performance of the classifier [18]. The researchers calculated severity scores for 173 dermoscopic images of skin lesions with known histological diagnosis. A cutoff score was used to measure the sensitivity and specificity of the classifier. The study found that the classifier had a sensitivity of 97.4 % for melanoma. The limitations of this study are that the image dataset was small and that it was retrospective, using available images selected by a dermatologist for biopsy.

The literature review revealed the following significant limitations and research gaps in the studies. In particular, the limited datasets for ML and DL-based skin disease classification and the lack of a complete system for preprocessing methods for medical images. For the effective performance of ML and DL models, image normalization, preprocessing, data augmentation, and their balance are important processes. Also, many studies have relied solely on the accuracy index to evaluate the performance of the model. Although accuracy is a crucial indicator, additional criteria including sensitivity, specificity, precision, and F1 score can provide a more comprehensive assessment of the model's performance. In addition, in some studies, the proposed models only achieved good results on a specific database. The fact that the accuracy of the model is not general in the detection of skin diseases limits the scope of the study.

II. Methodology. According to the results of the researches and the literature review, researchers mainly used the following five main steps in computer-aided diagnosis of skin diseases: image acquisition, pre-processing, segmentation, feature extraction, and classification.

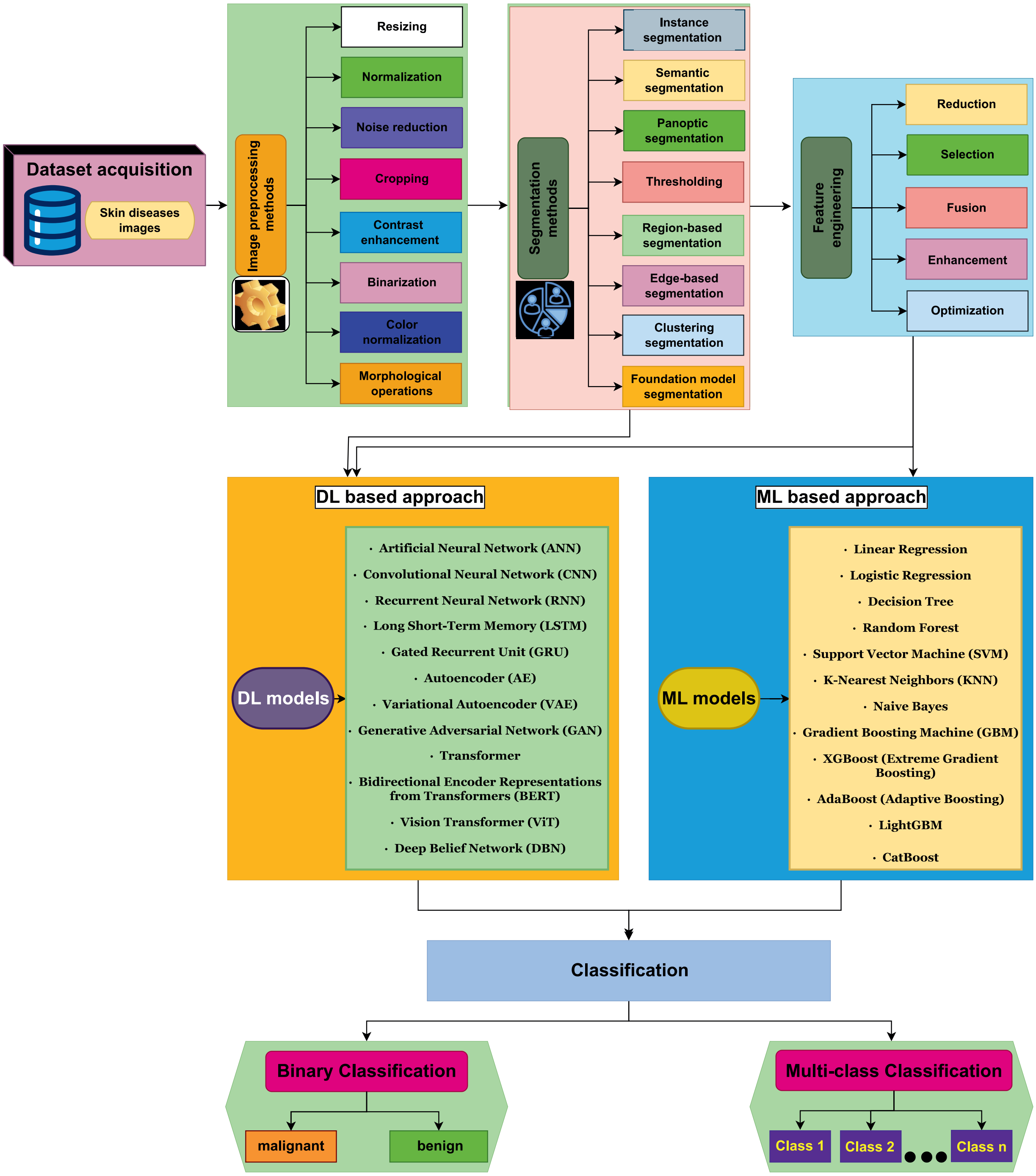

Fig. 2. Process step flow architecture for skin disease classification

The most important steps in computer-aided diagnosis of skin diseases are segmentation and classification. The process flow architecture and common methodology for detecting and classifying skin diseases using image datasets using ML and DL techniques are illustrated in the following figure (Figure 2).

2.1. Image pre-processing. Medical image processing technologies play an important role in medicine for dermatological diagnostics and research. The process of processing medical images includes many methods to improve their quality and facilitate analysis. Pre-processing of medical images obtained from the skin surface is an important step to remove noise from the image and improve image quality. The main goal of this step is to improve the quality of skin disease images by removing unnecessary and irrelevant parts of the image. A good choice of processing technique can significantly improve the accuracy. The following is an analysis of pre-processing methods for acquired medical images.

Image Resizing. Image resizing refers to the process of changing the dimensions (width and height) of a captured digital image. The main goal of image resizing is to reduce or increase the size while preserving as much image detail and clarity as possible. There are several methods for resizing images, each with different approaches to preserving quality, sharpness, and image detail.

Normalization. Image normalization is an important process in machine learning and is the process of adapting images to certain standards in order to reduce errors in model performance. In this case, before entering images into the model, their pixel values are brought to a certain range. This range is usually from 0 to 255 for images with an 8-bit depth, where 0 represents black and 255 represents white. Normalization is performed to improve the contrast of the image or to standardize pixel values for further processing. As a result, the model is able to read the received data more stably and faster. At the same time, errors that occur during calculation are prevented. The following methods of image normalization are widely used in practice.

1. Min-Max normalization. In this method, the largest and smallest pixel values of the image are found and adjusted to a certain range. The general formula for normalizing images in the range [0; 1] is as follows:

$$Normalized_{value} = \frac{Pixel_{value} - Min_{value}}{Max_{value} - Min_{value}} \tag{1}$$

To normalize images in the range [-1; 1], the above formula is modified as follows:

$$Normalized_{value} = 2 * \frac{Pixel_{value} - Min_{value}}{Max_{value} - Min_{value}} - 1 \tag{2}$$

Here,

1) $Pixel_{value}$— the original pixel value in the image.

2) Min_{value} — the minimum pixel value (or normalized range) in the image.

3) Max_{value}— the maximum pixel value (or normalized range) in the image.

2. Z-score normalization. This normalization method assumes a Gaussian distribution of the data and transforms the features to a mean (μ) of 0 and a standard deviation (σ) of 1. The formula for Z-score normalization is:

$$Normalized_{value} = \frac{Pixel_{value} - \mu}{\sigma} \tag{3}$$

Here, $Pixel_{value}$ — the original pixel value in the image, μ — the mean value in the image, σ — standard deviation in the image.

This method is particularly useful when working with algorithms that assume normally distributed data, such as many linear models. Unlike the min-max scaling technique, this standardization technique is not limited to a specific range. This normalization technique mainly represents features in terms of the number of standard deviations away from the mean [19].

3. Mean normalization. In the mean normalization method, the pixel values of an image are adjusted to zero by adjusting them to the mean value of the data set. This ensures a balanced distribution of the image data.

$$Normalized_{value} = \frac{Pixel_{value} - \mu}{Max_{value} - Min_{value}} \tag{4}$$

Here, $Pixel_{value}$ — the original pixel value in the image, μ — the mean value in the image, Min_{value} — the minimum pixel value (or normalized range) in the image, Max_{value}— the maximum pixel value (or normalized range) in the image.

4. Decimal Scaling. Decimal scaling is a method of scaling image data by reducing a set of image data with a constant high intensity value to smaller manageable values. This method simplifies large pixel values by dividing them by powers of 10. This is an efficient way to scale data without complex calculations [20].

$$Normalized_{value} = \frac{Pixel_{value}}{10^j} \tag{5}$$

Here,

1)$Pixel_{value}$ — the original pixel value in the image.

2) The scale factor j is the smallest integer, and it is defined as follows:: $10^j \geq |I_{max}|$

5. L2 Normalization. The L2 normalization method is also known as Euclidean normalization. The L2 norm (Euclidean norm) of pixel intensity is a method of scaling image data so that it is equal to 1. This method is commonly used in machine learning, deep learning, and image processing to normalize image features. The L2 normalization for pixel intensity is performed as follows:

$$Normalized_{value} = \frac{Pixel_{value}}{\|I\|_2} \tag{6}$$

Here,

1) $Pixel_{value}$ — the original pixel value in the image.

2) $\|I\|_2$ is the L2 norm of the pixel intensity and it is defined as: $\|I\|_2 = \sqrt{\sum_{i=1}^{N} I_i^2}$

Noise reduction. Noise in medical images can hinder the interpretation of medical scans and lead to misdiagnosis. Therefore, noise reduction in medical images is a very important task. The quality of medical images such as CT, MRI, X-ray, endoscopic images, and dermatological images is crucial for accurate diagnosis and treatment. Noise reduction methods should ensure the preservation of important details such as anatomical structures or pathological features, while eliminating distortions in the image that enter the model. The goal of image noise reduction is not only to remove noise, but also to preserve clinical details. The main requirements for image denoising [21]:

- Smooth areas should remain smooth.
- Protect image boundaries (prevent blurring).
- Preserve texture information.
- Preserve overall contrast.
- Prevent new artifacts from appearing.

Noise reduction methods are classified as follows, based on the noise reduction approaches [22]:

1) Filtering method;
2) domain method;
3) Statistical method;
4) Machine Learning (ML) methods.

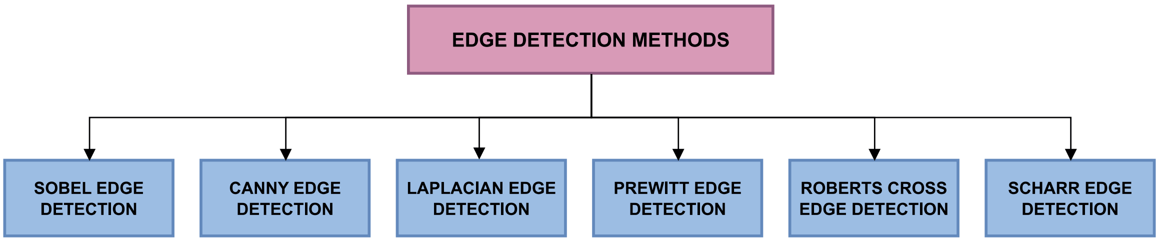

Fig. 3. Edge detection methods

Edge detection. Edge detection is a basic image processing technique that is used to detect and locate the boundaries or contours of objects in an image. This technique is used to detect discontinuities in brightness intensity in an image and extract the contours of objects in the image. The boundaries of any object in an image are usually defined as regions where the brightness intensity changes sharply. The main goal of edge detection is to distinguish these regions [23]. There are various methods for edge detection, which are illustrated in Figure 3 below:

Contrast enhancement. Contrast enhancement improves the visibility of objects in an image. This process is accomplished by increasing the difference in brightness between image objects and their background.

Contrast enhancement is typically done in two steps: 1) Contrast stretch: This method improves brightness differences evenly across the entire brightness range of the image.

2) Tonal enhancement: This step increases the brightness differences in specific areas of the image (shadow (dark), midtone (gray), or highlight (light) parts) at the expense of brightness differences in other areas.

Contrast enhancement makes objects in an image stand out more clearly and makes them more visible. The following table lists several techniques and methods for image contrast enhancement (Table 2).

Binarization. The main purpose of image binarization is to clearly and efficiently extract important information from complex medical images, which is an important factor in speeding up the diagnostic and analysis processes and increasing the accuracy of the results. It is also a medical image processing technique used to convert grayscale or color images into binary images. Binary images have only two pixel values: 0 (black) and 1 (white). This technique is widely used to highlight important features in an image, segment specific regions, or simplify medical image analysis.

Color normalization. Color normalization is the process of averaging the color changes from one image to another. There are many different normalization algorithms, including histogram specification, Reinhardt's method, Macenko's method, spot color descriptor (SCD), full color normalization, structure-preserving color normalization (SPCN), and many others [24].

Morphological operations are techniques used in image processing that focuses on the structure and shape of image components. These techniques process images based on their shapes and are mainly used in binary images, but they can also be used for grayscale images. The basic idea is to use structural elements to analyze an image and modify pixel values based on the spatial location and shape of a structural element. Erosion, expansion, opening, closing, and other important morphological processes serve various purposes in image enhancement and evaluation [25]. The modification and analysis of shapes and structures within images

Table 2

Contrast enhancement techniques and methods

Image Contrast Enhancement Techniques and Methods	Histogram Equalization	Global Histogram Equalization (GHE)	This method spreads out the intensity values of an image's histogram to utilize the full range of possible values, enhancing the overall contrast.
		Adaptive Histogram Equalization (AHE)	This variant improves local contrast and brings out more detail by applying histogram equalization to smaller regions within the image.
		Contrast Limited Adaptive Histogram Equalization (CLAHE)	This method is designed to overcome noise amplification issues in AHE by limiting the contrast enhancement in homogeneous areas.
	Linear Contrast Stretching	Min-Max Stretching	Involves transforming the intensity values to cover the full range available, usually from 0 to 255 in an 8-bit image.
		Mean and Standard Deviation Stretching	Adjusts image contrast based on the mean and standard deviation of pixel intensities, ensuring a balanced distribution around the mean value.
	Gamma Correction	Power-Law Transformations	Utilizes a parameter called gamma to correct the brightness level. Gamma <1 enhances images with dark regions, while gamma >1 enhances images with light regions.
	Piecewise Linear Contrast Stretching	Contrast Stretching with Multiple Breakpoints	Divides the intensity range into segments and applies different linear transformations to each. This allows more nuanced adjustments to different parts of the image.
	Logarithmic and Exponential Transformations	Log Transformation	Useful for enhancing details in the darker regions of an image.
		Exponential Transformation	Helps enhance bright areas by applying exponential scaling.
	Unsharp Masking		Enhances contrast by increasing the brightness difference around edges. This method sharpens the image and makes details more prominent.
	Retinex Theory	Single Scale Retinex (SSR) and Multi-Scale Retinex (MSR)	Aims to mimic human visual perception by enhancing both global and local contrast in varied illumination conditions.

is accomplished using morphological analysis, a powerful tool in image processing. These techniques are useful in a variety of applications, including pattern recognition, computer vision, and medical imaging, as they can be used to enhance image features, remove noise, and identify existing patterns.

2.2. Segmentation. Image segmentation is a computer vision technique that aims to simplify and analyze digital images by dividing them into groups of pixels. Segmentation is the process of dividing or separating any digital image into multiple parts (segments). The goal of image segmentation is to present it in the simplest possible form and make it highly informative for analysis. There are several methods for image segmentation, with edge segmentation being one of the simplest and most effective. In this method, the pixels of the image are separated according to the contrast of the image, mainly based on intensity, and then a specific area of the image is divided into segments based on the application.

Today to achieve image segmentation, traditional and deep learning methods, as shown above (Figure 4), are used widely. These methods also include several methods in their place.

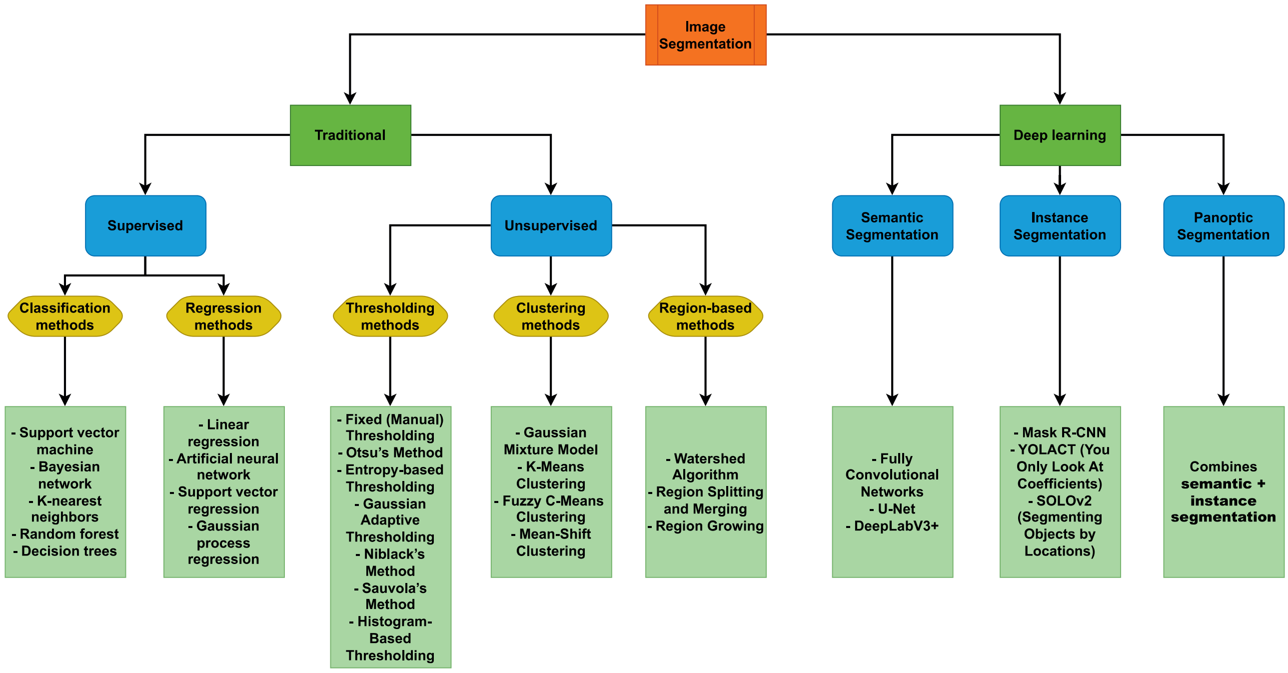

Fig. 4. Image segmentation methods [26]

Taking into account the complexity of the problem and the characteristics of the image, one of the appropriate methods is selected and image segmentation is achieved.

2.3. Feature extraction. After the segmentation step, feature extraction is the next major step, which is the input to neural classifiers. Data cannot be directly fed to a neural classifier for classification, only the extracted features are given as input. Feature extraction and feature selection are very laborious tasks that require a lot of time, effort, and human resources. Selecting the right features is very important because the performance of an ML classifier depends on the features. There are many feature extraction methods that can be used before feeding the dataset to an ML classifier for the classification task. These include stationary features, morphological features, wavelet-based features, color-based features, local and global features, and others. The most commonly used feature extraction methods for skin disease detection task are texture-based features, gray-level co-occurrence matrix (GLCM), asymmetry, boundary, color, and diameter (ABCD) rule-based features, principal component analysis (PCA) features, and geometric features. However, most researchers have used a combination of several features to achieve good classifier performance.

Feature extraction is the most important task in the classification task using ML classifier. However, this step is not important for DL-based classifier because DL classifiers extract features automatically. However, several researchers have used feature extraction techniques to further improve DL-based classifiers in the detection of various skin diseases. Some researchers have achieved good results in the classification of skin diseases using DL techniques without using any feature extraction methods.

2.4. Classification. ML-based classification has been proven to be one of the best methods for skin disease detection. Many researchers have identified skin disease types using ML-based classifiers, but various types of preprocessing, segmentation, and feature extraction methods are used in the pre-classification process. The research results show that many researchers have achieved even better accuracy using ML classifiers for skin disease classification than DL classifiers. The most effective and commonly used ML classifiers for skin disease detection are Support Vector Machine (SVM), Random Forest (RF), SVM with Radial basis kernel (SVM-RBF), Adaptive Artificial Neural Network (AANN), Radial Basis Function Neural Network (RBFNN), Ensemble Classifier (EC), Decision Tree (DT), K-Nearest Neighbor (KNN), etc [44].

DL is a highly trainable method that does not require any input features. Deep learning models are preferred for skin disease detection tasks, especially for detecting skin diseases from large datasets of images. The use of DL models has increased significantly in recent decades, especially for object detection and segmentation tasks. The most commonly used DL models for skin disease detection and classification tasks are Convolutional neural networks (CNN), Deep convolutional neural networks (Deep CNN), Long short term memory networks (LSTM), AlexNet, Residual Network (ResNet), UNet, VGG, Explainable Artificial Intelligence (EAI), EfcientNetB1, ShufeNet [45].

III. Comparative analysis of results. The literature review and the studies conducted suggest that integrating ML and DL approaches for classifying skin diseases into dermatological practice will allow for early detection and treatment of diseases. Tables 3–4 below provide a comprehensive comparative analysis of the methods based on ML and DL algorithms proposed by researchers for classifying skin diseases. The tables analyze 20 studies with important parameters such as the type of disease, pre-processing methods for medical images, optimal classification methods, used database, number of data, percentage of highest scores (accuracy), and similar parameters.

Table 3 it can be observed the some types of skin diseases detection based on ML algorithms have been studied from the recently published peer review articles. According to the table, the authors in [30] used Extreme Learning Machine (ELM) classifer as the machine learning model for the detection of melanoma from 10015 numbers of skin images to produce 97.68 % accuracy. CAM integration was used in Spatial-autoencoder and FFT-autoencoder to effectively filter out noise and extract the most important features in the spatial and frequency domains. The ELM classifier is employed after feature extraction, for the subsequent classification. Authors in [29] also achieved 97.8 % accuracy for the detection of types of skin cancer like BCC, SCC and melanoma using Support Machine Learnig (SVM) as ML classifer. The Low accuracy % reported by among all types of skin diseases detection technique is 67 % for acne detection. For acne detection, the lowest accuracy reported is 67 % using Logistic Regression classifer and the authors in [32] utilized 3000 skin image dataset.

So, based on the state-of-art analysis Table 3, it was observed that the highest accuracy of classifcation for the skin diseases detection was achieved of 97.8 % by three diferent types of skin cancers, BCC, SCC, melanoma. Where all these have used diferent types of ML based classifer, diferent types of dataset and diferent types features extraction techniques during the detection process.

All the studied literature on the detection of skin diseases was analyzed using the methods considered in the above tables. According to it, researchers M. Vidya, Maya V. Karki achieved high results in the diagnosis of skin cancer based on ML classifiers using 1000 image samples. The study used the Geodesic Active Contour (GAC) image preprocessing method. The evaluation indicators are high in all respects, and the accuracy of the SVM classifier is 97.8 %.

In DL-based approaches, researchers Himanshu K. Gajera et al. developed the DenseNet-121 with multi-layer perceptron (MLP) model for melanoma classification and achieved the

Table 3

Classification of skin diseases using ML algorithms

Sn	Type of skin diseases	Preprocessing	Dataset	Data samples	Training data	Test data	Algorithm	Metrics	References	Year
1	BCC, SCC, melanoma	Automatic Grabcut Segmentation, digital hair removal (DHR), Gaussian filtering	ISIC 2019 challenge dataset	25331	80 %	20 %	SVM KNN DT	Accuracy = 95 % 94 % 93 %	[27]	2022
2	Melanoma	Gaussian filter va median filter, k means clustering	ISIC 2019 challenge dataset	25000	70 %	30 %	Multi-class Support Vector Machine (MSVM)	Accuracy= 96.25 %, precision= 96.32 %	[28]	2020
3	Acne, cherry angioma, melanoma, psoriasis	Otsu's, for extracting features Gabor, Entropy, and Sobel	Private data	377	80 %	20 %	SVM KNN RF	Accuracy= 90.7 % 84.2 % 67.1 %	[10]	2022
4	BCC, SCC, melanoma	Geodesic Active Contour (GAC)	International Skin Imaging Collaboration (ISIC)	1000	-	-	SVM KNN Naïve Bayes	Accuracy= 97.8 %	[29]	2020
5	Melanoma	Dual-autoencoder	HAM10000	10015	80 %	20 %	Extreme Learning Machine (ELM)	Accuracy= 97.66 %, precision= 97.68 %	[30]	2024
6	BCC	Pre-trained CNN	ISBI 2016	1952	85 %	15 %	SVM	Accuracy= 88.02 %	[31]	2023
7	Acne	-	Private data	3000	80 %	20 %	Logistic Regression	Accuracy= 67 %	[32]	2019
8	eczema, psoriasis,	Segmentation	DermIs DermQuest DermNZ	1800	-	-	SVM, Quadratic SVM	Accuracy= 94.74 %	[33]	2019
9	Melanoma	ABCD rule	PH2	200	80 %	20 %	ANN SVM KNN DT	Accuracy= 92.50 % 89.50 % 82.00 % 90.00 %	[34]	2017
10	Lupus Erythematosus	LASSO dimensionality reduction	Private data	136	70 %	30 %	Xgboost	Accuracy= 82 %	[35]	2023

highest accuracy acc 98 %. The study used the PH2 dataset as a database. Preprocessing of medical images was performed using methods such as ABCD, Boundary Localization, Image Resize and Normalization.

Conclusion. This research paper analyzes approaches based on ML and DL technologies for early detection and classification of skin diseases based on medical images. The study focuses on common and dangerous types of skin diseases. Different ML and DL architectures used for classification of skin diseases are discussed, and the processes leading up to the classification stage, that is, pre-processing methods for medical images, are studied. As a conclusion of the study, it is possible to create complex models that can analyze dermatological images with a high level of accuracy using ML and DL algorithms based on image analysis. These models are expected to support dermatologists with their ability to classify various changes in the skin with high accuracy and identify dangerous skin diseases. The use of

Table 4

Classification of skin diseases using DL algorithms

Sn	Type of skin diseases	Preprocessing	Dataset	Data samples	Training data	Test data	Algorithm	Metrics	References	Year
1	Melanoma	data augmentation techniques	HAM10000	10000	85 %	15 %	MobileNet V2 with the LSTM	Accuracy = 84.12 %	[36]	2021
2	BCC	data augmentation techniques	HAM10000	10000	85 %	15 %	MobileNet V2 with the LSTM	Accuracy = 96.63 %	[36]	2021
3	psoriasis	Resizing, normalisation	Private data	813	80 %	20 %	ResNet50V2, ResNet101V2, ResNet152V2	Accuracy= 91.41 % 89.63 % 90.24 %	[37]	2024
4	psoriasis	Resizing, normalisation	Private data	813	80 %	20 %	CNN Ensemble Model	Accuracy= 93.29 %	[37]	2024
5	Lupus	-	The National Centre for Biotechnology (NCBI)	330	70 %	30 %	attention-based CNN, Stacked Bi-LSTM	Accuracy= 95 % 92 %	[38]	2024
6	Eczema, Melanoma, psoriasis,	Resizing	Xiangya-Derm	150223	-	-	Convolutional Neural Network (CNN)	Accuracy= 87.42 %	[39]	2023
7	melanoma	ABCD, Boundary Localization, Image Resize and Normalization	PH2	200	70 %	30 %	DenseNet-121 with multi-layer perceptron (MLP)	Accuracy= 98 %	[40]	2023
8	SCC, melanoma	-	ISIC dataset	57536	80 %	20 %	Inception-ResNet-v2 CNN	Accuracy= 89.3 %	[41]	2022
9	BCC, melanoma	Segmentation, filter	HAM10000	10000	80 %	20 %	S^2C-DeLeNet	Accuracy= 97.41 %	[42]	2022
10	Eczema, psoriasis	Resizing, Gaussian blur	DermNet and HAM10000	27153	80 %	20 %	CNN	Accuracy= 96.20 %	[43]	2023

computer-aided diagnostic systems can help dermatologists detect complex skin lesions at early stages and make decisions. Future research should focus on classifying skin diseases based on AI approaches and improving the accuracy and robustness of models, and integrating these technologies into the current healthcare infrastructure.

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