IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

A Review Of Machine Learning Techniques On Skin Lesion Diagnosis

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Abstract -Skin lesions affect millions of individuals globally, presenting challenges in diagnosis due to their similar symptoms. This study aims to gather and analyzethe use of machine learning (ML) in skin lesion research, aiming to spur the development of automated systems for skin disease diagnosis. Several skin image datasets have been created to aid dermatologists in clinical diagnosis, leading to the development of automated diagnosis systems utilizing image segmentation and classification techniques. This paper provides an overview of the essential steps in skin lesion diagnosis. It reviews the applications of ML methods, including traditional ML and deep learning (DL), in skin disease recognition, highlighting their contributions, methodologies, and outcomes. Such analysis supports the ongoing advancement of reliable and efficient computer-aided skin disease diagnosis systems. With further re-search, these automatic skin diagnosis studies are expected to be integrated into real clinical settings in the near future.

I. INTRODUCTION

The skin, being the body's largest organ, serves as a vital defence mechanism against external threats like bacteria, viruses, and toxins. Skin disorders, affecting individuals across age groups, stem from diverse factors like genetics, lifestyle choices, and environmental influences [1]. Examples of prevalent skin conditions encompass acne, skin cancer, seborrheic keratosis, psoriasis, melanoma, and vitiligo, as illustrated in Figure 1.

Figure 1: Common types of skin disease

Skin diseases, due to their widespread impact, can severely affect both the physical and mental health of individuals. Therefore, precise and prompt diagnosis holds paramount importance for effective management. However, certain skin conditions still pose challenges in diagnosis and treatment. For instance, diseases like skin cancer and vitiligo can be elusive to diagnose in their early stages due to the absence of distinct pathological features. The conventional diagnostic methods heavily rely on visual inspection and subjective assessments, which may lack precision and objectivity [2], leading to potential misdiagnosis even by dermatologists. Moreover, in remote regions with limited access to dermatologists, non-specialists often handle dermatological cases with inadequate training and resources, despite the availability of reference materials. The shortage of dermatologists and the uneven distribution of healthcare resources exacerbate the difficulties in achieving accurate diagnoses in underserved regions.

AI technology based on image recognition has emerged as a promising tool for diagnosing skin diseases. These algorithms can be trained using large datasets of skin images to learn disease patterns, potentially providing more accurate diagnoses, especially in early stages. Additionally, AI algorithms can offer more objective diagnoses by avoiding human biases through careful design and debugging [3]. This technology has the potential to address some of the challenges associated with diagnosing skin diseases, particularly in underserved areas lacking dermatologists. Common AI algorithms used for this purpose include machine learning (ML) and deep learning (DL), both capable of identifying repetitive features of skin lesions for accurate diagnosis of both benign and malignant conditions. While DL typically performs better with large and complex datasets, ML methods remain useful in situations with limited data. These methods can be integrated into computer-aided diagnosis (CAD) systems, providing accurate classification results for dermatologists. Moreover, for non-specialists, such systems can mitigate errors stemming from their limited expertise [4]. Hence, it is crucial to explore the advancements and recent accomplishments of machine learning (ML) and deep learning (DL) techniques in dermatological diagnosis. This examination can help identify existing challenges and suggest suitable recommendations to propel advancements in this field. Figure 2 illustrates the typical schematic diagram of the automated skin image diagnosis procedure.

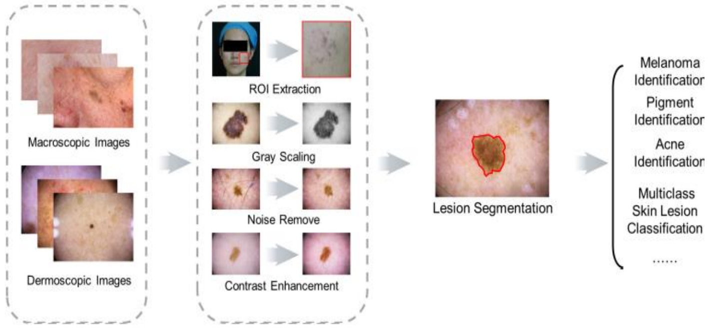

Figure 2: Schematic diagram of skin image diagnosis.

A.Skin Lesion Datasets and Image Preprocessing

Educational institutions and medical organizations have generated datasets of various sizes and types of skin lesions to develop skin diagnosis models. These datasets double as educational platforms [5] for the public and as testing grounds for new diagnosis algorithms. However, images often contain artifacts like hair, varying illumination, circular markings, and black frames, which degrade image quality and impede analysis. To address these challenges, image pre-processing techniques are employed, including resizing, grayscale conversion, noise removal, and contrast enhancement, either individually or in combination. These techniques typically enhance both the efficiency and effectiveness of diagnosis, as well as the processes of segmentation and classification. Image resizing is a common approach to handling images with diverse sizes, allowing most images to be standardized to similar dimensions. Furthermore, deep learning (DL) methods excel at managing images with varying sizes [6]. For instance, Convolutional Neural Networks (CNNs) exhibit translation invariance, enabling trained models to accommodate different image scales without compromising performance. Consequently, researchers can confidently address skin classification and segmentation tasks across a wide range of image sizes. Image resizing involves standardizing the pixel count and cropping irrelevant portions of the image before extracting the area of interest (ROI). This not only reduces computation time but also facilitates subsequent diagnosis tasks. To mitigate the impact of varying skin tones, scaled photos are often converted to grayscale images [7]. Different filters, as depicted in Figure 3, can be applied to eliminate various types of noise artifacts. For ROI determination, a monomorphic filter can enhance contrast and equalize image brightness. Hair removal filters are selected based on hair features: thick hairs can be addressed with inpainting techniques, while more hair can be removed using the Dull Razor method. Gaussian, average, and median filters are effective for thin hair removal.

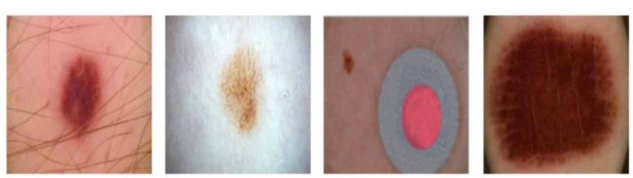

Figure 3: Images with various types of noise

In Figure 3c, colored circles in some photos can be detected and filled in with healthy skin. Morphological region filling is a typical approach for replacing the black framing observed in the corners of Figure 3d [8]. Contrast enhancement for ROI determination after noise removal is achieved using a bottom-hat filter and contrast-limited adaptive histogram equalization. Another common technique for preprocessing facial skin lesions involves face parsing, which entails eliminating the mouth, nose, eyes, and eyebrows before conducting the study.

B.Skin Lesion Segmentation

Segmenting the region of interest (ROI) is a critical initial step in accurately classifying and extracting informative features from skin lesions during the diagnosis process. Conventional image segmentation techniques utilize pixel, region, and edge-based methods to remove skin lesions from images. Pixel-based segmentation techniques such as binary or Otsu thresholding categorize each pixel into two groups (skin lesion or healthy skin). However, the discontinuous results often observed, particularly in dermoscopic images, are mainly due to low contrast and smooth transitions between healthy skin and lesions [9]. Region-based segmentation involves merging or expanding regions to create skin lesion regions by recognizing nearby pixels. Expansion starts at a seed point and extends region coverage by examining neighboring pixels, while merging combines adjacent pixels with similar intensity levels. However, due to the diversity in color and texture of skin lesions, these methods can be challenging to apply effectively. Edge-based techniques, like the watershed algorithm, use intensity differences between neighboring pixels to define lesion borders. Yet, they are prone to noise from factors like skin texture, hair, and air bubbles, leading to convergence issues and inaccurate segmentation results, especially in noisy areas. Segmenting images with noise, low contrast, and diverse color and texture can pose challenges for conventional segmentation techniques to achieve accurate results [10]. To address this, fuzzy logic, neural networks (NNs), and evolutionary computation have been proposed for ROI segmentation, mimicking human reasoning, natural evolution, and learning processes. These techniques can be employed individually or in combination to improve segmentation outcomes. For example, the fuzzy approach has been utilized to segment dermoscopic images using both splitting and merging strategies. By incorporating fused color and texture information, this combination achieved unsupervised perceptual segmentation.

C.Skin Lesion Classification

Skin lesion analysis classification tasks typically fall into two categories: binary classification, focused on early melanoma detection for prompt treatment, and multi-class classification, aiming to identify various skin diseases. Similar sizes, textures, colors, and shapes among different lesions, along with significant correlation levels, often present challenges in classification [11]. Both traditional machine learning (ML) methods and deep learning (DL) methods can be employed, but ML necessitates feature extraction and selection.

D. Feature Extraction and Selection

Feature extraction and selection aim to identify an optimal feature set with excellent discrimination capability for classifying skin lesion images. Expert knowledge and clinical experience are preferred, as they can effectively guide this process. Image processing algorithms can generate features useful for classification, but the effectiveness of these features depends on the specific disease symptoms and diagnosis tasks. Various methods are explored to extract color, texture, edge, and shape features for accurate melanoma diagnosis [12]. The well-known ABCD rule selects traits based on the understanding that melanoma exhibits multiple colors and forms, an irregular border, an asymmetrical shape, and a diameter greater than 6 mm. Specifically, the letters A, B, C, and D represent asymmetry, border, color, and diameter, respectively. Another mnemonic, CASH, is used to extract similar qualities such as color, architecture, symmetry, and homogeneity. Additionally, a three-point checklist approach has been proposed, focusing on unusual network patterns, blue-white structures, and asymmetry of color and structure for melanoma diagnosis. This approach was later expanded to a seven-point checklist by including factors like lesion size, itchiness, or changes in sensation.

Color features can be extracted from various color spaces, including HSV (hue, saturation, value), YCbCr (luminance and chrominance), and also the blue-difference and red-difference chroma spaces, along with grayscale space. Texture features, typically derived from grayscale images, reflect the surface roughness of lesions [13]. Methods such as the gray-level co-occurrence matrix (GLCM) can quantify texture characteristics like contrast, correlation, energy, and homogeneity. Additionally, the neighborhood grayscale difference matrix can provide insights into coarseness, busyness, complexity, and texture strength. Moreover, the shape and edges of skin lesions can be evaluated for uniformity or regularity using techniques like the histogram of oriented gradients (HOG). However, while many extracted image elements are based on expert knowledge and real-world experience, they may not completely and accurately depict skin lesions. Therefore, the efficacy of such features should be carefully considered for each specific task, as the same feature set may not perform effectively under different conditions [14]. For example, features extracted from the ABCD rule might achieve high accuracy in melanoma detection but may not be as effective in classifying various skin diseases. Furthermore, the presence of superfluous or noisy data can lead to extraneous characteristics that diminish the overall precision of the diagnosis. Hence, selecting representative feature subsets tailored to the research requirements and the available data is crucial. Ultimately, this approach can aid in constructing a classification model that is simpler, performs better, and requires less training time.

E. ML Models for Skin Disease Classification

In classification tasks, ML algorithms as illustrated in figure 4 utilize selected and extracted features as inputs as. Following feature selection, classic ML models such as Support Vector Machines (SVM), Naïve Bayes (NB) classifiers [15], and K-nearest neighbor (KNN) are commonly applied to categorize skin conditions or differentiate melanoma from pigmentation.

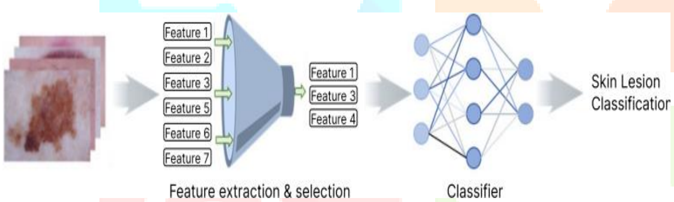

Figure 4: Traditional ML-based skin lesion classification

Overall, these traditional ML methods with their standardized structures often deliver satisfactory precision and accuracy outcomes. Support Vector Machines (SVM) categorize skin lesions by establishing a decision plane to separate different classes using extracted color, texture, shape, and edge features. K-nearest neighbor (KNN) distinguishes between normal skin and skin lesions by comparing the similarity of input features. Tree-structured classification methods like Decision Tree (DT) and Random Forest (RF) can handle non-numeric features derived from the ABCD [16] rule, such as asymmetrical shape and irregular border.Naïve Bayes (NB) classifies skin lesion images into their respective disease categories based on the highest probability.

II. LITERATURE REVIEW

D. A. Reddy, et.al (2023) suggested an innovative model for improving the process to detect skin disease [17]. The initial stage was to segment the image and extract the features from diseased lesions. Thus, an autoencoder (AE)-based classifier was implemented. The Optimized Region Growing (ORG) was employed for segmenting the Diseased lesions on the basis of Grey Wolf Optimization (GWO). The Gray Level Co-occurrence Matrix (GLCM) and Weber Local Descriptor (WLD) models were deployed for extracting the texture features from the segmented lesion. In the end, the latent representation generated via AE was employed for creating an alleviated feature set. An integrated convolutional neural network (CNN) algorithm was assisted in classifying the diseased lesions from latent illustration. The experiments demonstrated that the suggested model was performed well as compared to other methods.

V. D. Midasala, et.al (2024) presented a skin cancer detection and classification (SCDC) model called MFEUsLNet in which multilevel feature extraction (MFE)-based artificial intelligence (AI) was utilized with unsupervised learning (USL) to detect skin diseases [18]. At first, the bilateral filter was utilized to pre-process skin images for eliminating the artifacts from the source images. At second, the skin lesions were segmented using a popular USL method known as K-means clustering (KMC) for diagnosing the diseased skin lesion in an effectual way. At third, the gray level co-occurrence matrix (GLCM), and redundant discrete wavelet transform (RDWT) models were implemented to extract texture and color features of lower level. At last, recurrent neural network (RNN) algorithm was deployed for training based on multi-level features and classifying various kinds of skin cancer. The experiments on ISIC-2020 dataset confirmed the supremacy of presented model over traditional methods concerning accuracy, specificity, precision, recall, F1-score and sensitivity.

T. Swapna, et.al (2021) formulated a mechanism in which deep learning (DL) methods, namely convolutional neural network (CNN) and 3 predefined algorithms: AlexNet, ResNet, InceptionV3 were employed for diagnosing skin diseases [19]. A dataset, containing images of 7 diseases: melanoma, nevus, seborrheic keratosis etc., was generated to classify skin diseases. The images of cuts and burns were inserted to expand this dataset after classifying them as skin diseased images in traditional methods. The employed methods were effective for mitigating the effort of humans, in which features were extracted manually and data was reconstructed to classify images. A training set was created using variance and its size was maximized to attain superior accuracy. The experimental results indicated that the second algorithm had offered higher accuracy as compared to others to detect skin diseases.

A. Rushi, et.al (2023) discussed that detecting diseases at initial stages and accurately was required to cure and prevent their transmission [20]. A system was developed to detect skin disease in which potentials of convolutional neural networks (CNN) and support vector machine (SVM) were exploited. The initial algorithm was trained for extracting features from skin lesion images and the next algorithm was fed with these features to classify the skin diseases. A huge dataset containing skin lesion images was employed to train the first algorithm and the extracted features were assisted in training the next algorithm. The simulation results exhibited that the developed system yielded superior accuracy, sensitivity, and specificity in comparison with existing techniques and proved effectual to diagnose skin diseases.Moreover, the reliability of this tool was proved to detect skin diseases at initial stage and effectively to manage and cure critical conditions. The developed system had lower time complexity and its suitability was proved for diverse applications in ultrasound skin imaging and computer-aided diagnosis (CAD) systems.

S. S. A, et.al (2022) analyzed that the process to diagnose skin disease in recent times had undergone diverse pathological laboratory tests to recognize precise disease [21]. Therefore, Convolutional Neural Network (CNN) algorithm was constructed and implemented to recognize 7 skin diseases, such as Melanocytic Nevi, Melanoma, Benign keratosis-like lesions, Basal cell carcinoma, Actinic keratoses, Vascular lesions, and Dermatofibroma. The MNSIT: HAM10000 datasets was generated from Kaggle to simulate the projected algorithm. In this dataset, numerous images related to every diseases class were comprised in undefined numbers. The experimental results revealed that the constructed algorithm was worked reliably and offered higher accuracy to detect skin diseases.

B. Kalpana, et.al (2023) introduced an ensemble support vector kernel random forest-based hybrid equilibrium Aquila optimization (ESVMKRF-HEAO) method to detect skin diseases [22]. The HAM10000 dataset was employed to compute the introduced method in which diverse skin lesions images were comprised. Primarily, this algorithm aimed to eliminate intrusions and noises in the dataset, and the preprocessing pipelines were utilized to enhance the image qualities. Subsequently, the thresholding-based segmentation method was assisted in segmenting the cancerous lesion regions from the normal background. Eventually, the introduced method was employed for predicting and classifying the segmented images on the basis of their feature characteristics into 5 diverse classes: melanocytic nevus, basal cell carcinoma (BCC), melanoma, actinic keratosis (AK) and dermatofibroma. MATLAB 2019a was executed for simulating this method. The results depicted that the introduced method offered an accuracy of 97.4% and higher sensitivity, f-1 score, accuracy, precision and specificity.

M. Ahammed, et.al (2022) devised a digital hair removal (DHR) method on the basis of morphological filtering (MF): Black-Hat transformation (BHT) and inpainting algorithm to detect skin diseases [23]. Thereafter, Gaussian filtering (GF) was applied for de-blurring and denoising images. Moreover, an automatic Grabcut method was implemented for segmenting the infected lesions. The input features were extracted from the skin images through Gray Level Co-occurrence Matrix (GLCM) and statistical features methods. These features were deployed in 3 machine learning (ML) methods, namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Decision Tree (DT) to classify skin images into melanoma (MEL), melanocytic nevus (NV), basal cell carcinoma (BCC), actinic keratosis (AK), benign keratosis (BKL), dermatofibroma (DF), vascular lesion (VASC), and Squamous cell carcinoma (SCC). ISIC 2019 challenge and HAM10000 datasets were employed to compute the devised method. The results indicated that the devised method offered an accuracy of 95% and 97% using first method, 94% and 95% with second, and 93% and 95% with last method on both datasets respectively.

L. Wan, et.al (2022) intended a fusion network (FN)-based algorithm to diagnose pigmented skin disease [24]. Firstly, the images of generated dataset were pre-processed. Secondly, the image was flipped and image style was transmitted for augmenting the images so that the imbalance among diverse categories was mitigated in the dataset. Lastly, a comparative analysis was conducted on feature-level fusion optimization (FLFO) approaches relied on deep features in contrast to others. The Gradient-weighted Class Activation Mapping (Grad_CAM) and Grad_CAM++ techniques were adopted to visualize the images and compute the intended algorithm. The experimental results validated that the intended algorithm offered an accuracy of 92.1% and Area Under Curve (AUC) of 95.3%. Furthermore, this algorithm was proved adaptable and accurate to detect skin disorders, and applicable in real-time applications.

G. Gao, et.al (2024) presented an information bottleneck theory for guiding convolution operations which retained the relevant skin lesion information and filtered out redundant details [25]. A view selection technique was deployed for selecting an integration of RGB, HSL, and YCbCr from 7 opinions. A multi-view compression and collaboration (MCC) model was designed depending upon 2 methods. This model helped the Convolutional Neural Network (CNN) to eliminate label-independent information and enhance the image visions. Consequently, the skin diseases were detected more effectively. The HD and the ISIC2018 datasets were employed for evaluating the designed model. The simulation demonstrated that the designed model detected the skin cancer at higher accuracy, precision, recall, and F1-score with CNN. Besides, this model was useful for clinical specialists to detect skin diseases in medical practice, so that the healthcare services and quality of life were improved.

M. W. P. Maduranga, et.al (2022) established a deep learning (DL) model called Convolution Neural Networks (CNN) for detecting and classifying skin diseases on the HAM10000 dataset [26]. This model was worked effectively to detect skin diseases. A mobile application was developed to take an action precisely and quickly. The image of infected region of a skin diseases was recognized at initial stage to help patients and specialists to verify the type disease. This model was resilient to diagnose infected area quickly at 2 times fewer computations and at lower computation efforts. In analysis, the MobileNet with transfer learning (TL) had provided an accuracy up to 85% while detecting skin disorders automatically. The experiments reported that the established model was effective for doctors to detect skin disorders in fast and precise way with the help of smart phone.

TABLE I

COMPARISON OF EXITING APPROACHES

Author	Year	Technique Used	Dataset	Parameters	Results	Limitations
D. A. Reddy, et.al	2023	Autoencoder (AE)-based classifier, Optimized Region Growing (ORG)	ph21	Accuracy and precision	The experiments demonstrated that the suggested model was performed well as compared to other methods.	Only 200 images were employed in the given dataset.
V. D. Midasala, et.al	2024	MFEUsLNet	ISIC-2020 dataset	Accuracy, specificity, precision, recall, F1-score and sensitivity	The experiments on ISIC-2020 dataset confirmed the supremacy of presented model over traditional methods concerning accuracy, specificity, precision, recall, F1-score and sensitivity.	This model was not capable of detecting large or extensive range of ailments.
T. Swapna, et.al	2021	A mechanism with deep learning (DL) methods	ImageNet dataset	Accuracy	The experimental results indicated that the second algorithm had offered higher accuracy as compared to others to detect skin diseases.	This mechanism was unsuitable to detect all kind of skin lesions.
A. Rushi, et.al	2023	A system having Convolutional neural networks (CNN) and support vector machine (SVM)	Medical image dataset	Confusion matrix, and ROC curve, time complexity	The simulation results exhibited that the developed system yielded superior accuracy, sensitivity, and specificity in comparison with existing techniques and proved effectual to diagnose skin diseases.	These methods were not effective of handling certain images.
S. S. A, et.al	2022	Convolutional Neural Network (CNN)	MNSIT: HAM10000	Accuracy	The experimental results revealed that the	This algorithm consumed much time to

					constructed algorithm was worked reliably and offered higher accuracy to detect skin diseases.	detect the diseased portion from image.
B. Kalpana, et.al	2023	ESVMKRF-HEAO method	HAM10000 dataset	Sensitivity, f-1 score, accuracy, precision and specificity	The results depicted that the introduced method offered an accuracy of 97.4% and higher sensitivity, f-1 score, accuracy, precision and specificity.	This method was not efficient for detecting skin diseases in real-time.
M. Ahammed, et.al	2022	Black-Hat transformation (BHT) and inpainting algorithm	ISIC 2019 challenge and HAM10000	Accuracy	The results indicated that the devised method offered an accuracy of 95% and 97% using first method, 94% and 95% with second, and 93% and 95% with last method on both datasets respectively.	An automated algorithm was employed in segmenting images that was not accurate always while detecting the skin lesion.
L. Wan, et.al	2022	A fusion network (FN)-based algorithm	HAM10000	Accuracy and AUC	The experimental results validated that the intended algorithm offered an accuracy of 92.1% and Area Under Curve (AUC) of 95.3%.	This algorithm was not worked robustly while detecting skin diseases from high definition images.
G. Gao, et.al	2024	A multi-view compression and collaboration (MCC) model	ISIC2018 dataset and HD dataset	Accuracy, precision, recall, and F1-score	The simulation demonstrated that the designed model detected the skin cancer at higher accuracy, precision, recall, and F1-score with CNN.	The computation complexity was higher.
M. W. P.	2022	CNN-based	HAM10000	Accuracy	The	This research

Maduranga, et.al		method	dataset		experiments reported that the established model was effective for doctors to detect skin disorders in fast and precise way with the help of smart phone.	was planned on the basis of traditional dataset and capable of detecting only 7 kinds of skin diseases.

III. CONCLUSION

The skin, being the body's largest organ, serves as a vital defense mechanism against extern The realm of AI-based skin lesion diagnosis has garnered significant attention, largely propelled by the availability of suitable methods and continuously up-dated datasets. Despite addressing pertinent topics over the past decade, numerous areas warrant further investigation and improvement. This paper undertakes a review of publicly available skin lesion datasets, the employed image preprocessing techniques, and subsequent methods for skin lesion segmentation and classification. It also discusses the current status, challenges, and future prospects in ML-driven skin disease diagnosis. Such studies serve to catalyse the development of advanced concepts and methodologies. In conclusion, future trends in image segmentation and classification of skin lesions necessitate the creation of more comprehensive datasets, exploration of robust models, especially for macroscopic image recognition, and the implementation of methods for increasingly reliable automated diagnosis.

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