Grenze International Journal of Engineering and Technology, January Issue

Development and Performance Enhancement of Machine Learning based Approaches for Detection of Skin Diseases: A Survey

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***Abstract*—Skin diseases represent a major health challenge, and early detection is essential for successful treatment. Machine learning (ML) has emerged as a valuable tool in enhancing diagnostic accuracy. This study explores the application of Machine Learning for skin disease classification, emphasizing both image processing and clinical feature analysis. This article reviews the techniques and methods used to diagnose common skin conditions. Additionally, it has covered the assessment metrics for the performance analysis of different diagnosis systems as well as the image databases that are available. While feature based approaches consistently achieve accuracy above 94%, image-based methods show varied results ranging from 50% to 100%. Despite progress, issues such as data quality and model generalization persist. This review identifies key areas for further investigation and highlights the potential of Machine Learning to transform dermatological diagnostics. With the wide array of clinical and histopathological patterns observed in Papulosquamous skin disorder, precise differentiation is critical for accurate diagnosis and the development of effective, tailored treatment plans. The analysis provides an insightful overview of the relevant studies from the literature, highlighting the critical research gaps that have been identified to detect single skin lesion and imbalance dataset.**

***Index Terms*—Skin lesion, Machine Learning Approaches, Deep Learning Network, Papulosquamous skin Lesion disorders.**

I. INTRODUCTION

The human skin, the body's largest organ, spans an impressive average of 16,000 cm in adults and makes up around 8% of total body weight. This dynamic organ serves as the body's first line of defence but faces constant threats, including UV radiation, inadequate sunscreen application, heat-induced rashes, persistent itching, lesions, dark patches, and numerous infections. Given its exposure to environmental and internal stressors, skin conditions are among the most common health concerns, emphasizing the need for consistent care and preventive measures. The human skin condition is the major part in our bodies, encompassing a dermis, the outermost layer of lymphatic systems, tissues beneath the skin, nerves, muscles, and blood vessels.

Grenze ID: 01.GIJET.11.1.255

Far beyond serving as a robust defence against a spectrum of threats, from germs, viruses, reactions, to bacterial and fungal illnesses, it exhibits a dynamic transformative nature. This transformative quality enables the skin to adapt and influence its texture in response to the ever changing interplay with external elements [1], [2]. The outer layer of the skin, acting as a formidable defence, protects against viruses, germs, allergies, and fungal infections, signalling their intrusion through swelling, itching, redness, and burning typical signs of a skin infection. Papulosquamous disorders characterize a diverse and morphologically substantial group of skin conditions, largely due to their common occurrence. Accurate diagnosis hinges on the careful evaluation of two key morphological elements: the pattern of tissue reaction and the nature of the inflammatory response.

Its contribution can be distilled into the following key points: MD, PhD, Professor

By consolidating research articles published between 2014 and 2024, this study presents vital perspectives on the detection, segmentation, and classification of skin lesions. This survey summarized and evaluated the contributions and limitations of the past survey papers in the domain of Papulosquamous skin classification and type-oriented detection techniques, which were published between 2014 and 2024.

This review summaries unaddressed research needs, contribution a brief summary of the unresolved research challenges and potential avenues for further exploration in Papulosquamous skin condition categorization and detection across diverse skin datasets.

The study paper highlighted the remarkable advancements in the accuracy of skin image analysis achieved through machine learning methods in recent years, thereby establishing it as a complementary approach to clinical evaluation metrics. This combined analysis is essential for proper interpretation of skin biopsies. These disorders encompass a broad range of noninfectious, erythematous, papular, and scaly lesions, including conditions such as psoriasis, lichen planus, pityriasis rosea, and pityriasis rubra pilaris (PRP).

Certain conditions, particularly psoriasis, can present in multiple clinical variants, often resembling other dermatological disorders and complicating diagnosis. The wide variety of clinical presentations seen in papulosquamous diseases makes thorough clinical evaluation, coupled with histopathological examination, critical for accurate diagnosis and effective treatment planning.

Psoriasis is a long-lasting skin disorder marked by the appearance of thick, itchy, and scaly patches, which frequently develop on the knees, elbows, scalp, and trunk. Although it is relatively widespread, psoriasis has no definitive cure. The condition can lead to physical discomfort, impact sleep quality, and hinder daily activities. Psoriasis tends to occur in cycles, with active flare-ups persisting for weeks or months, followed by periods of remission. For those genetically susceptible, triggers such as infections, skin trauma (like cuts or burns), and certain medications can provoke or intensify flare-ups, making management challenging.[1][5].

Lichen planus emerges as an inflammatory papulosquamous condition that uniquely affects both the skin and mucous membranes. It predominantly targets areas like the skin, nails, and mucosal surfaces, while refraining from involving internal organs. Noteworthy is its heightened occurrence in women. Oral lichen planus, in particular, warrants close attention due to its heightened propensity for progressing to oral cancer, emphasizing the critical role of clinical classification in ongoing surveillance. For a correct diagnosis and successful treatment, histology studies in detail reveal characteristic signs which include saw-tooth rete lines, atrophy, acanthosis, hyper orthokeratosis, with melanin incontinence [2].

A single, oval-shaped patch on the face, chest, belly, or back commonly referred to as a (herald patch) is frequently the initial symptom of pityriasis rosea . While sickness can strike anyone at any age, it most frequently strikes those in the 10 to 35 age range. Usually, the rash goes away on its own in ten weeks. In contrast, limited regions of skin remained unaffected by pityriasis rubra pilaris (PRP), an uncommon inflammation illness that manifests as unusual. PRP is further characterized by the presence of follicular papules with thickened skin (hyperkeratosis) and keratoderma affecting the palms and soles. PRP is further considered by the presence of follicular papules with thickened skin (hyperkeratosis) and keratoderma affecting the palms and soles. [1],[4]. Papulosquamous skin illnesses has mirror other conditions of the skin and have a wide range of clinical signs, they are famously difficult to diagnose. This overlap often leads to diagnostic ambiguity and increases the likelihood of misdiagnosis. In addition to their physical impact, these conditions can severely affect patients' mental health, social interactions, and general well-being, creating emotional strain not only for the individual but also for their loved ones. With the wide array of clinical and histopathological patterns observed in these psoriasis, lichen planus , pituris rubra pilaris and pituris rubra diseases, precise differentiation is critical for accurate diagnosis and the development of effective, tailored treatment plans. . The analysis provides an insightful overview of the relevant studies from the literature, highlighting the critical research gaps that have been identified The proposed work has major implications for improving the precision and efficiency of dermatological examinations, which play a critical role in the early stage diagnosis of Papulosquamous skin disorders in related work.

II. LITERATURE REVIEW

Several researchers have dedicated their efforts to the domain of skin disease detection and prediction, with notable contributions are as follows:

In this study [7], a 50-layer ResNet model was implemented by using Keras library with 2.8.0 version on the TensorFlow framework, with its effectiveness evaluated through fivefold and threefold cross-validation, as well as random data splits. To improve the dataset's variety and mitigate class imbalances, advanced data augmentation and class balancing techniques were employed. The model was designed to differentiate between psoriasis and lichen planus skin conditions, leveraging the deep learning capabilities of the 50-layer Residual Network. The results demonstrated a notable accuracy of 89.07%, with sensitivity and specificity reaching 86.46% and 86.02%, respectively.

This paper leveraged machine learning (ML) techniques to address practical challenges. In the study [8], a two-step approach was employed: initially, the ReliefF algorithm was utilized for optimal feature selection, followed by the application of the K-nearest neighbour (KNN) algorithm to forecast outcomes based on the chosen features. An erythemato-squamous benchmark dataset containing psoriasis, seborrheic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, and pityriasis rubra pilaris was used for experimental evaluations. A significant improvement in classification accuracy was seen, as the model outperformed conventional KNN draws near, obtaining remarkable results such as 94.59% accuracy, 90.94% recall, 94.72% precision, a 92.79% F-score, and a Kappa coefficient of 93.20%.

Aijaz et al. [9] used a trailblazing strategy to develop two innovative deep learning algorithms, notably the Convolutional Neural Network (CNN) and the Long Short erm Memory (LSTM). These algorithms were used to perform the difficult task of categorizing different forms of psoriasis based on color and texture attributes. The study rigorously used a publicly available dataset, which included 172 photos of healthy skin from the BFL NTU collection and an additional 301 photographs with psoriasis from the Dermnet dataset. The outcome of this unique deep learning application displayed extraordinary accuracy, with CNN obtaining an impressive 84.2% accuracy and LSTM achieving 72.3% accuracy.

This study [10], utilized a dataset of 13,603 dermoscopic images annotated by dermatologists, spanning 14 disease categories such as lichen planus, rosacea, viral warts, and basal cell carcinoma. The EfficientNet-b4 architecture, pre-trained on ImageNet, was employed as the CNN backbone with a tailored 14-output neuron classification layer. The model, implemented in PyTorch, included seven auxiliary classifiers at various intermediate layers. To better understand the model's decision-making, saliency maps were constructed to visualize the attention areas, and t-SNE was employed to explore the internal feature representations with accuracy accuracy of 0.948, sensitivity of 0.934 and specificity of 0.950.

In this paper used the Deep Learning Neural Networks with MobileNet V2 and LSTM" employs a grey-level co-occurrence matrix to analyze the progression of skin diseases. The proposed approach integrates MobileNet V2 with Long Short-Term Memory (LSTM) networks to achieve effective classification and detection of skin conditions while minimizing computational demands. In testing with real-time images from Kaggle, the model attained an accuracy of 85.34%, demonstrating its competitive performance compared to other methodologies. In addition, the study investigated a number of neural network architectures, such as an upgraded convolutional neural system architecture, using the Visual Geometry Group's Very Deep Convolutional neural networks Networks (VGG) for massive operations image recognition, Fine-Tuned Neural Networks (FTNN), and Convolutional Neural Networks (CNN)[11].

In this research, 4 new Error Correcting Output Code (ECOC) techniques one-versus-all, binary complete, one-versus-one, and ternary complete were introduced in this study [12] to tackle the problem of imbalanced multiclass classification. The dataset utilized encompassed clinical and histopathological data from 6 specific skin diseasesUsing real-world data, a Bayesian Optimized Support Vector Machine (BO SVM) model was used to diagnose epidermal skin disorders (ESDs).

The Bayesian Optimization (BO) process was conducted within a Gaussian Process (GP) probabilistic framework, employing a Matern ARD 5/2 kernel for covariance modeling, paired with the Expected Improvement (EI) acquisition strategy to enhance optimization results.

This study [13] presents an innovative method for diagnosing skin conditions using a dual-input convolutional neural network (CNN). The model builds on a modified VGG-19 architecture, integrating dual input layers and batch normalization to enhance classification accuracy.

To ensure a fair comparison, batch normalization was also applied to the standard VGG-19 model. Without this enhancement, both models demonstrated poor learning performance and marginal accuracy gains. Trained over 150 epochs with the same parameters and methodologies, the dual-input CNN achieved an impressive classification accuracy of 94%, outperforming the original VGG-19 model, which only reached 89% accuracy when trained from scratch.

So that provide us with various study, in Table I, of the papulosquamous skin disorder not only affect physical health but also have significant psychosocial and quality-of-life implications. In previous study's emphasis on these one or two specific skin conditions placed a higher priority on their precise identification rather than seeking inflated overall accuracy. The results used architecture along with the results from the various studies has been listed in the Table I below. The following are used to compare the performance of the architectures used in this study with the exciting architectures. A convolutional neural network (CNN) combined with VGG19 architecture is used by the authors in response to this, and it achieves an accuracy rate of 89% in skin disease detection, compared to 94% using the double input model [13].

Thus, the study not only sheds light on diagnosing these diseases early (at the first stage) is important but also presents how new-age machine learning methodologies, specifically deep learning and computer vision, can enhance severity and sensitivity of skin disease classification in Table I. Several researchers have dedicated their efforts to the domain of skin disease detection in cases one or two diseases considers for that to find out their diagnostic accuracy and prediction, with notable contributions are as follows in Table I.

TABLE I: LITERATURE REVIEW

Authors	Year	Diseases Name	Model/Technique	Results
Arshia Estkandari et .al. [7]	2024	Psoriasis and Lichen Planus	ResNet model with 50 layers	Achieved accuracy = 89.07%, sensitivity = 86.46% and specificity = 86.02%.
Alotaibi, Abdullah S.[8]	2022	psoriasis, seboreic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, and pityriasis rubra pilaris	Hybrid Model : ReliefF Algorithm with KNN	Achieved = 94.59% , Recall= 90.94% , Precision =94.72% ,F-score= 92.79% ,Kappa's coefficient =93.20%
Syeda Fatima Aijaz et.al.[9]	2022	psoriasis	CNN with (LSTMs).	Achieved =84.2% and LSTM achieved =72.3% accuracy.
Chen Yu Zhu et al. [10]	2021	14 categories of diseases, namely lichen planus (LP), rosacea (Rosa),viral warts (VW), acne vulgaris (AV), keloid and hypertrophic scar (KAHS), eczema and dermatitis (EAD), dermatofibroma (DF), seborrheic dermatitis (SD), seborrheic keratosis (SK), melanocytic nevus (MN), hemangioma (Hem), psoriasis (Pso), port wine stain (PWS),and basal cell carcinoma (BCC).	Google's EfficientNet-b4with ImageNet	Accuracy = 0.948, sensitivity of 0.934 and specificity of 0.950
Parvathaneni Naga Srinivasu et. al. [11]	2021	Melanocytic nevi, Benign keratosis-like lesions, Dermatofibroma, Vascular lesions, Actinic keratoses, Intraepithelial carcinoma, Basal cell carcinoma, and Melanoma	VGG19	Accuracy achieved with 85%
AM Elsayad, AM Nassef, M Al-Dhaifallah[12]	2022	They are six different diseases: psoriasis, seborrheic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, and pityriasis rubra pilaris	SVM, BO, and ECOC frameworks.	Training and test accuracies of 98.81% and 99.07%, respectively
G. G Sanjeevi,, T.R. Tharun Raj and S. Malarkhodi[13]	2021	actinic keratosis basal cell carcinoma and other malignant lesions, atopic dermatitis, bullous disease, cellulitis impetigo	VGG19	Model has accuracy =89%, while the dual input model has 94%
Lu et al. [14]	2023	psoriasis	SVM) and Markov random field (MRF)	81.79% sensitivity and 87% specificity
Murugan et al.[15]	2019	melanoma	SVM, Random Forest and kNN Classifiers	89.43 (SVM) 76.87 (RF) 69.54 (KNN).
Rastogi et. al.[16]	2024	rosacea, actinic keratosis, basal cell carcinoma, eczema, and acne on face	CNN, Deep CNN and random forest models	Accuracy =56.21%
P. Achararit et al[17]	2023	oral lichen planus (OLP) and non-OLP	Xception model	Accuracy= 82–88%.
Faghihi et al[18]	2024	melanoma	VGG16 and VGG19	accuracy, sensitivity, specificity, average precision, and balanced

				multiclass accuracy improve by 1.6%, 24.4%, 3.6%, 23.2%, and 5.6%, respectively
Prottasha et.al.,[19]	2023	Eczema ,Psoriasis	Inception, ResNet V2	Training Accuracy =99.7% Accuracy=97-1%
Ahammed et. al. , [20]	2022	melanoma	melanoma	Accuracy of SVM= 95%, KNN=94%, and DT=93% for the ISIC 2019 HAM10000 dataset accuracy of SVM=97%, KNN=95%, and DT= 95%

III. ANALYTICAL RESULTS

The originality of this research lies in addressing a specific gap, which emerges from the scarcity of studies that exclusively focus on these two particular lesions[7], without incorporating other types of skin conditions. While most existing research investigates a wide range of dermatological diseases, few have concentrated solely on these lesions in isolation. There is a scarcity of high-quality and diverse datasets for training machine learning models in skin care[1],[3],[8] .

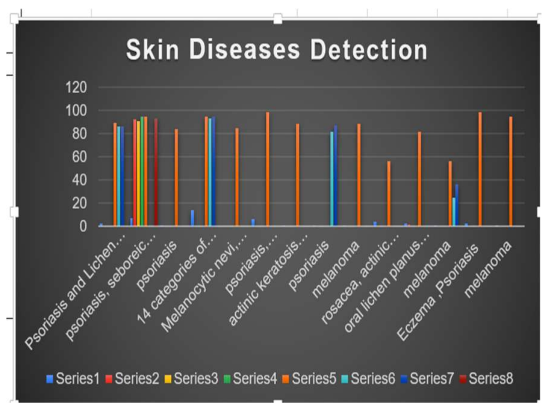

Figure 1. Skin Diseases Detection Accuracy with performance evaluation metrics

Difficulty in same symptom appears skin disease detection methods are related to disease elements that include color of the skin, bubbles of air, nails, along with hairs etc.[2],[3],[7],[8]. Using performance accuracy, the most advanced machine learning and deep learning techniques used for diagnosing a specific disease is determined in Figure 1.

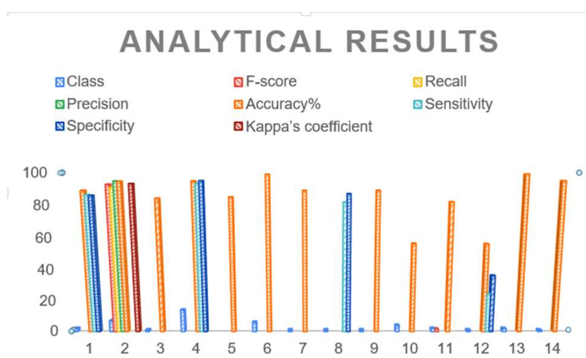

Figure 2. Compare analytical results for different skin diseases and models used in research

It is shown the assessment metrics and image databases that are accessible for the performance analysis of different diagnosis of skin diseases systems like psoriasis, Lichen, Seboreic Melanoma, oral lichen planus and Eczema etc. By narrowing the scope, this study allows for a more detailed and precise investigation, paving the way for the creation of specialized models that are more accurate in diagnosing these papulosquamous skin diseases. Multiple clinical forms of papulosquamous illnesses might present diagnostic issues for physicians due to their variable morphological and dermatological characteristics. This study shows compare analytical results for different skin diseases and models used in research with performance metrics which is shown in Figure 2.

IV. Skin Diseases Data Collection and Data Pre-Processing

Many existing Studies used diverse and comprehensive dataset of dermatological images, including various skin conditions. During data collection process, the images will be collected from Dermnet (http://www.dermnet.com/), kaggle, PH2, HAM10000, Google photos and live image data which is available from the hospital etc. Following steps are required to detect skin diseases detection .

Data Preprocessing: It is a stage for improving the image. Pre-process the images by resizing, normalizing, noise removal and enhancing contrast to ensure consistency and quality. An uncommon inflammatory skin condition that causes single or multiple linear bands of pink or red papules to appear on the skin. A chronic inflammatory autoimmune disease that affects the skin, nails, scalp, and mucous membranes. The skin disease detection system, involves pre-processing tasks such as noise reduction, contrast enhancement, region of interest (ROI) segmentation, and feature extraction.

To accurately isolate skin lesions, lightweight segmentation algorithms are used in existing studies, also including median filtering, Gaussian filtering and fast-marching painting algorithm for remove unnecessary parts, etc.

Data Augmentation: Apply data augmentation techniques, such as rotation, scaling, flipping, adjusting image contrast, adjusting image brightness, adjusting image sharpness and applying filter to increase the dataset's diversity.

Data Splitting: Split the dataset into training and test sets.

Feature extraction: An essential stage in pipelines for machine learning and image processing is feature extraction. For applications such as classification, detection, segmentation, and identification, it converts unprocessed picture data into a collection of representative characteristics that machine learning models may exploit.

In order to perform tasks like detection and classification of skin diseases, feature extraction extracts important features from images.

Typical methods involve like pictures into frequency domains using Discrete Cosine Transform (DCT) and Fast Fourier Transform (FFT). Examine the asymmetry, border, color, and size of medical images using the ABCD/ABCDE Rules. Extract gradient-based features and texture using GLCM, HOG, and LBP.

V. Performance Metrics

The performance of any test system is usually measured using the confusion matrix through accuracy, sensitivity, specificity (Estkandari , 2024; Aijaz, 2022; Zhu, 2021; Faghihi, 2024; S Murugan ,2019 ; Lu, 2023; Prottasha, 2023). Test accuracy gives the measurement of the overall correctness of the proposed work, which is calculated as the ratio of the sum of correct clusters to the total clusters and is shown in Equation (1):

$$\text{Accuracy (\%)}= \frac{TP+T}{TP+TN+FP+FN} * 100 \qquad (1)$$

Where:

True Positive (TP): Person with a lesion identified as a True Positive (TP).

TrueNegative(TN): A healthy individual is reported to be healthy.

False Positive (FP): A healthy individual suspected of having a lesion.

True Positive (FN): Lesion individual identified as healthy is a True Positive (FN).

Test sensitivity (or Recall):It is the ratio of correctly recognized sick individuals to the estimated total number of sick individuals, providing the percentage of sick individuals that are accurately diagnosed as unwell define in Equation(2):

$$\text{Sensitivity or Recall(\%)} = \frac{TP}{TP+F} * 100 \qquad (2)$$

Test specificity: It is the ratio of correctly recognized healthy individuals to the estimated total number of healthy individuals, provides the percentage of healthy individuals who are accurately identified as healthy by following equation(3) :

$$\text{Specificity(\%)} = \frac{TN}{TN+FP} * 100 \qquad (3)$$

Precision: It is the ratio of accurately predicted positive observations to all predicted positives. It is also known as Positive Predictive Value which is shown in equation (4).

$$\text{Precision(P)} = \frac{TN}{TP+F} \quad (4)$$

F1-Score:- When the dataset is unbalanced, the F-score (F1-score) is a statistic used to assess a classification model's accuracy. It offers a fair assessment of both precision and recall by taking the harmonic mean of the two which is shown in equation (5).

$$f1 - Score = 2 * \frac{Precision * Recall}{Precision + Recal} \quad (5)$$

Since accuracy scores were reported in the majority of the works, this paper displayed accuracy for comparison sake in this evaluation.

VI. An Overview of the State of the Art Diseases Detection System

An overview of different methods for detecting skin diseases is provided in Table 1. Disease types, methodology (segmentation, feature extraction, classification), accuracy, limitations and the most appropriate approach to become state-of-the-art for a particular skin condition are all included.

We can see from the above table that there are numerous approaches to skin disease detection.

Nevertheless, some methods (such the active contour model + ABCD rule + SVM+RF+CNN+) are effective for a few skin conditions. However, the approaches used by some automated systems were not adequately explained, and several systems failed to measure the accuracy. Based on the detection accuracy, we have ranked the best-fitting algorithm.

Challenges: There are specific issues with dermatological photos that make it hard for computers to recognize skin lesions. The most prevalent artifacts in photos include oil bubbles, reflections, hair, variations in lighting, and various skin tones. Due to the variety of looks and characteristics, certain diseases are challenging to distinguish because of the low color contrast between the foreground (lesion) and backdrop (healthy skin). The system's accuracy will be reduced if the data sets are inadequate. Furthermore, the machine learning algorithms will not be able to accurately diagnose the disease if the segmentation is inadequate. Furthermore, it should be mentioned that in addition to image data, clinical test results are also necessary for skin illnesses.

VII. Conclusion

Skin diseases identification and detection of various skin disorders, the researchers ought to concentrate more on the application of hybrid models with effective, trustworthy, and accurate methods. In conclusion, special attention is required to design a more generic detection mechanism.

Thus, the Papulosquamous disorders have diverse morphological and dermatological conditions as they present with numerous clinical variants and pose to be a diagnostic dilemma for the clinician. In some cases, invasive muscle biopsy procedures is required to diagnose the skin diseases which can be burdensome for patients. After studying various papers, the aim of this research is to avoid the need for invasive muscle biopsy procedures for diagnosing papulosquamous skin diseases.

To address these challenges, in this research purpose to control varied data samples of skin diseases and employ advanced machine learning approaches to improve diagnostic accuracy. We propose the development of machine learning-based approaches for early-stage detection of papulosquamous skin conditions by using Vision Transformer (ViT) and YOLO based model.

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