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Deep into Accuracy: Exploring the Performance of Skin Detection Algorithms in Deep Learning

Rajat Mishra[1], Vandana Dixit Kaushik[2]

[1] Research Scholar, Department of Computer Science and Engineering, HBTU, Kanpur, India
[2] Professor, Department of Computer Science and Engineering, HBTU, Kanpur, India

Correspondence should be addressed to Rajat Mishra; rajatmishracse@hbtu.ac.in

ABSTRACT- Skin diseases rank among the most prevalent medical conditions, given that the skin, being the outermost layer of the body, is susceptible to rapid affliction. Timely identification of these diseases is crucial to prevent them from progressing to life-threatening stages. This review explores diverse research endeavors employing deep learning technology for skin disease identification. It provides a brief overview of skin diseases, encompassing their types, datasets used for skin disease research, and techniques for data preprocessing. The review delves into the realm of deep learning, elucidating prominent methods adopted by researchers for diagnosing skin diseases. Our primary objective is to furnish a systematic literature review of skin disease detection, emphasizing the utilization of deep learning methodologies in recent research. Notably recognized for their heightened accuracy, our observations affirm that these deep learning methods in skin disease image recognition surpass the capabilities of dermatologists, various machine-based therapeutic strategies, and alternative classification methods.

KEYWORDS- Convolutional neural network, Deep learning, Skin disease, diagnose skin disorder.

I. INTRODUCTION

The human skin, consisting of epidermis, dermis, and underlying tissues, is a prominent and vital aspect of the body. It acts as a sensory organ, sensing the external surroundings, and offers protection to internal organs and delicate tissues from harmful microorganisms, pollutants, and sun-related damage. Numerous external and internal factors can influence the condition of the skin. Skin diseases have a significant impact on both life and health. In addressing skin issues, individuals sometimes resort to home remedies, which may pose risks if unsuitable for the specific skin condition. Early intervention is crucial in managing skin problems, given their potential for easy transmission from person to person. Dermatological issues frequently constitute primary care concerns, with 8–36% of patients reporting at least one skin-related complaint. Skin disease is a distinct category of health concerns that has emerged as a global issue. Our expansive skin organ plays a crucial role as the body's primary defense mechanism, safeguarding against harmful substances, environmental factors, and the potential loss of essential nutrients [1]. Being the outermost layer of the body, it is susceptible to various factors like environmental conditions, bacterial and viral infections, direct exposure to UV radiation, weakened immune systems, fungal infections, contact with allergens, and interaction with individuals already affected by skin conditions. These elements adversely impact human health, compromise the functionality of the skin, result in specific skin impairments, and pose a risk to lives. Medical practitioners commonly depend on their expertise and individual assessments to form hypothesis about a patient's condition. Incorrect or delayed decisions could adversely impact the patient's well-being. Hence, there is an increasing demand to develop efficient approaches for early identification and management of skin conditions.. Technological progress has facilitated the organization and implementation of early-stage skin monitoring to detect various skin problems. Furthermore, due to its rapid advancement, computational intelligence software has swiftly become the preferred approach for analyzing patient data. Moreover, Deep Learning exhibits greater resilience and superior capabilities compared to traditional classifiers.

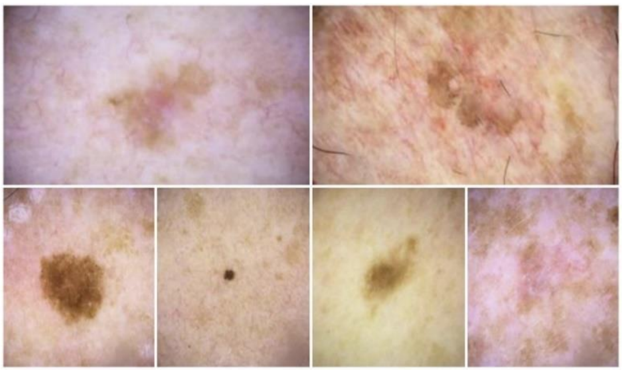

Figure 1: Skin Disease Pictures from dataset ISIC [2]

The big problem faced by the machines is classifying skin related images in absence of less data and methods. The changes spurred by the widespread integration of technology mirror the transformations ushered in by advancements in artificial intelligence (AI). In contemporary approaches, machine learning (ML) technology, as opposed to manual feature extraction, can be employed for classification tasks, resulting in time and effort savings. The increasing trend involves the application of ML methods in cancer diagnosis, where ML algorithms have boosted prediction accuracy. Within the realm of artificial intelligence, deep learning is rapidly expanding, offering numerous potential applications. Also the most influential and widely adopted techniques in machine learning for image recognition and categorization is deep learning.

Conventional machine learning (ML) methods, requiring extensive prior knowledge and prolonged preparation phases, are now less commonly employed. Classifiers based on deep learning can proficiently detect skin cancer in images, matching the effectiveness of dermatologists.

Deep learning models possess the ability to adjust to changing situations and autonomously identify features within the provided data, enabling them to effectively tackle various issues. Even with basic computer models, deep learning can utilize inferred data to detect and analyze patterns not explicitly presented to them, showcasing high efficiency. Skin-related diseases in dermatological images can be identified using supervised techniques like fuzzy systems and artificial neural networks (ANN), benefiting from feature extraction methods. Additionally, the k-nearest neighbors (KNN) classification method groups pixels based on their similarity in each feature image, aiding in distinguishing normal from abnormal images [3]. In response to these challenges, we have introduced deep learning algorithms that actively gather information and automatically extract features from data through feature extraction methods. These approaches yield precise diagnostic outcomes while addressing common issues related to feature extraction. Presently, convolutional neural networks (CNNs) in deep learning serve as the primary approach for skin disease image recognition, offering excellent superiority in feature representation.

Convolutional Neural Networks (CNNs) can play a crucial role in advancing computer-aided systems designed for skin lesion categorization, providing valuable assistance to dermatologists. However, a notable challenge is the scarcity of well-annotated training sets, especially for high-quality medical images, often attributed to the limited availability of thoroughly described photos for rare classes. Conventional CNNs may face difficulties in delivering effective performance with restricted datasets. Another significant obstacle is the computational costs associated with therapeutic applications. To address data overfitting, researchers employ pre-trained CNNs specifically tailored for skin lesion categorization. This involves integrating features from real-world photo datasets, such as ImageNet, into the trained CNNs.

This paper conducts a systematic literature review of recent research endeavors utilizing deep learning for skin disease diagnosis. The exploration starts with a comprehensive overview of skin issues, followed by an explanation of traditional techniques for data collection derived from literature research. Additionally, we explore various datasets for evaluating deep learning models in the domain of skin diseases. Convolutional Neural Network (CNN) techniques are employed to enhance and extend Deep Learning processes. Multi-hidden Layer Perceptrons (MLPs) within CNN layers perform multiple convolutions, Rectified Linear Unit (ReLU) operations, pooling, and connected layers.

An illustration of a method for diagnosing skin cancer is depicted in Figure 3.

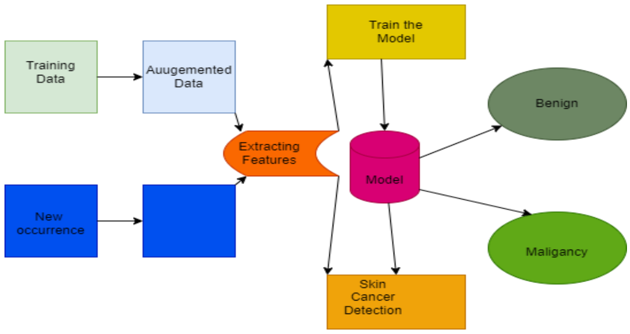

Figure 2: Cancer detection Process

II. LITERATURE REVIEW

In the methodology outlined in [4] for melanoma detection, the initial step involves extracting image features through computer vision. The system's accuracy is enhanced as a larger number of image features are extracted through this procedure. The methodology utilizes the Artificial Neural Network (ANN) technique, successfully identifying nine distinct types of skin diseases with an accuracy rate reaching up to 90%.

In [5], the focus of the author was on the examination of diverse segmentation techniques applicable for melanoma identification through image processing. The article discusses a segmentation procedure that leverages the boundaries of the affected area to extract additional information SVM is employed for classifying skin lesions by using PH2 dataset, achieving an accuracy rate of 92.5%.

An alternative effective strategy involves employing supervised techniques to enhance the model's generalization capability. Thurnhofer-Hemsi et al. [7] introduced a framework comprising an enhanced Convolutional Neural Network (CNN) and a standard grid aspect in their research on skin lesion identification. The approach utilizes a displacement method to create multiple sets of experimental image data, feeding them into individual predictors within ensembles, and then consolidating the conclusions from all classifiers for identification. When tested on the HAM10000 sample, the method exhibited an accuracy rate of 83.6%.

Researchers advocate for the application of image processing-based methods to distinguish various forms of skin ailments. In a study referenced as [6], a system was proposed for the segmentation of skin disorders through image analysis. This system employed two algorithms to detect affected skin areas and utilized an Artificial Neural Network (ANN) for disease classification.

In their study [12], researchers suggested an approach to classify various skin diseases utilizing a convolutional neural network pre-trained with GoogleNet Inspection V-3 (CNN). Their method involved clinical imaging datasets comprising both skin cancer and dermatoscopic images. Remarkably, their model outperformed human experts, achieving top-1 and top-3 classification accuracy rates of 60.0% and 80.3%, respectively.

Kumar et al. [13] devised a technique to evaluate skin infections by integrating machine learning and computer vision methods. The assessment of skin diseases utilizes machine learning, and computer vision is employed to extract features. The detection of infections involves the implementation of Region-based Convolutional Neural

Network techniques, encompassing three methodologies within it. The achieved accuracy of the results is 95%.

III. DATASETS IN DERMATOLOGY

Datasets in dermatology refer to collections of medical data specifically related to skin conditions and diseases. These datasets commonly comprise a varied collection of images, annotations, and pertinent details that Act as valuable assets for the training and assessment of ML models, specifically in the realm of dermatological image analysis.

Some well-known dermatology datasets include:

- HAM10000: This dataset comprises high-quality images featuring diverse skin lesions, encompassing melanoma and nevi.
- PH2 Dataset: This dataset includes dermoscopic images for the diagnosis of melanoma, with accompanying clinical information and expert-annotated ground truth.
- ISIC (International Skin Imaging Collaboration) Archive: This comprehensive archive encompasses skin images, incorporating dermoscopic and clinical photographs. It is specifically crafted to aid in the advancement of automated systems for skin cancer detection.
- DermQuest: A dataset comprising images of various skin conditions, useful for training and evaluating machine learning models in dermatology.

IV. DEEP LEARNING IN DERMATOLOGY

"Deep Learning in Dermatology" pertains to employing and implementing deep learning methodologies, a subset within artificial intelligence (AI) and machine learning (ML), within the dermatology domain. This entails leveraging sophisticated neural network architectures, comprehend convolutional neural networks (CNNs) and other models in deep learning, for the examination and understanding of dermatological data, particularly medical images depicting various skin conditions. As in Table 2 we illustrate the methods and approaches commonly employed in the integration of deep learning in dermatology.

V. DISCUSSION

Utilizing CNNs in skin disease detection offers several merits and advantages, particularly in the context of medical imaging.

Convolutional Neural Networks (CNNs) have gained widespread recognition and adoption in various fields, particularly in image and video analysis. Here are some merits or advantages of using CNNs in the context of deep learning. CNNs have demonstrated high accuracy rates in image classification tasks. Currently, a CNN network in deep learning is used as the principal approach for skin disease image recognition. Challenges in achieving timely and precise identification of skin conditions persist due to factors such as the need for extensive training, time constraints, and expertise required to employ various existing and emerging diagnostic approaches. Despite the development of numerous automated methods for skin disease diagnosis, a comprehensive decision support system is yet to be established. Presently, the primary approach for recognizing skin diseases in deep learning involves the utilization of a CNN network.

The findings of this research highlight the prevalent utilization of deep learning techniques in classifying and predicting skin diseases. While ongoing research is advancing various algorithms, deep learning methods, to a significant degree, demonstrate a higher accuracy rate in detecting skin diseases. Recognizing deep learning as an approach to enhancing overall outcomes is essential for improving patient diagnosis, treatment, and therapy. The comparison of accuracy for all algorithms is clearly presented in Table 1.

Table 1: Accuracy of different algorithms

Ref No.	Classification Techniques	Data Set	Accuracy (%)
8	Transfer learning	PH2	98.7
9	Full resolution Conv. Network	PH2	94.6
10	3D Color Text features	PH2	97.5
11	Alexnet + VGG16	Multiple	99%

VI. CONCLUSION

This paper explores several prominent machine vision and deep learning techniques that currently operate with a limited amount of available image data on skin diseases. The progress in deep learning signifies a notable advantage, providing trustworthy and accurate diagnoses, streamlining automated decision-making for swift and precise processing of medical data. The main focus of this study is to understand the utilization of deep learning methods in the diagnosis of skin disorders. DL models for classification and prediction exhibit the potential to minimize false positives in skin disease diagnosis, offering remarkably dependable and accurate results that mitigate potential risks to patients. Consequently, these models can play a crucial role in supporting patients and healthcare professionals globally, contributing to the enhancement of public health. Recent developments highlight the necessity for further work in areas such as feature representation, dimensional reduction, and minimal processing overhead to achieve the goal of faster and more accurate processing. An analysis of commonly used deep learning algorithms for skin disease detection, including their performance and accuracy comparison, indicates that deep learning models are notably more reliable, yielding more accurate results than alternative approaches and are widely employed in skin disease detection.

Table 2: Methods and approaches commonly employed in the integration of deep learning in dermatology

Method	Method Description	Application
Convolutional Neural Networks (CNNs):	CNNs find extensive application in image analysis and the extraction of features.	CNNs excel in recognizing patterns and features in dermatological images, enabling automated detection and classification of skin conditions.
Transfer Learning:	Transfer learning work on the utilization of pre-trained deep learning models on extensive datasets like ImageNet, adapting and refining them specifically for dermatological assignments.	Pre-trained models, such as VGG16, ResNet, or Inception, can be adapted to dermatological datasets, leveraging learned features for skin disease detection.
Autoencoders	Autoencoders are models for unsupervised learning, acquiring efficient representations of input data. Comprising an encoder and a decoder, they facilitate this learning process.	In dermatology, autoencoders can be used for dimensionality reduction and feature learning, aiding in the extraction of relevant information from skin images.
GANs	Generative Adversarial Networks, encompass a generator and a discriminator trained adversarially. Through this adversarial training, they have the capability to produce synthetic images that closely mimic real ones.	GANs, or Generative Adversarial Networks, can be utilized for generating supplementary synthetic dermatological images, contributing to the augmentation of datasets and enhancing the resilience of deep learning models.
Ensemble Learning	Ensemble learning encompasses the amalgamation of predictions derived from multiple models to improve overall performance.	Combinations of deep learning models, known as ensembles, offer more precise and dependable outcomes in tasks related to the classification of dermatological images.
Attention Mechanisms	Attention mechanisms concentrate on pertinent segments of an image during the processing stage, enhancing the interpretability of the model.	Attention mechanisms in deep learning models for dermatology help highlight specific areas of interest in skin images, aiding dermatologists in understanding model decisions.
Recurrent Neural Networks (RNNs)	RNNs, or Recurrent Neural Networks, are apt for processing sequential data and can be applied to analyze the temporal facets of dermatological conditions.	In cases where sequential information is crucial, such as tracking changes in skin lesions over time, RNNs can be employed.
Data Augmentation	Data augmentation involves creating variations of existing images through transformations like rotation, scaling, and flipping.	Augmenting dermatological datasets with variations enhances model generalization and robustness, especially when training data is limited.

CONFLICT OF INTERREST

The authors declare that they have no conflict of interest.

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