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A Comprehensive Review on Skin Disease Detection Using Convolutional Neural Networks and Transfer Learning Approaches

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Abstract—**Skin diseases represent a considerable part of the world health problem, as millions of people are affected by skin diseases, and skin diseases are visually similar and without easy access to dermatologists, present problems in terms of diagnostics. Convolutional Neural Networks (CNNs) and Artificial Intelligence (AI) in general have been the game-changer of automated skin disease detection. This paper aims to provide an overview of recent advances in the field of CNN and Transfer Learning (TL) approaches to classifying and diagnosing dermatological diseases based on dermoscopic and clinical images. It discusses datasets, preprocessing pipelines, CNN architectures, performance of different models, existing shortcomings, as well as future works. The key point of this review is to aid in creating AI-based web apps that would provide safe and efficient screening of skin diseases.**

Index Terms—**Skin Disease Detection, Convolutional Neural Networks (CNNs), Transfer Learning, Medical Image Classification, Dermoscopic Image Analysis.**

I. INTRODUCTION

Skin diseases are a huge problem affecting a great deal of the world population, thus causing a wide prevalence in healthcare systems, more so, in areas where dermatologists and skin specialists are few. They consist of painless as well as malignant disorders, like acne, eczema, psoriasis, vitiligo, and skin cancer (e.g., melanoma), and their visual symptoms are very similar, often causing diagnosis difficulties even to clinicians. The World Health Organization (WHO) identifies skin diseases as being part of the top 10 leading nonfatal disease burdens in the world, and millions of new cases are diagnosed every year.

Diagnosis of skin lesions can be labor-intensive, costly, and even expert interpretation dependent on the conventional methodology by use of physical examination, dermoscopy, and histopathological examination. The limitation of dermatologists in making timely or erroneous diagnoses is also worsened in rural or undeveloped regions. Applications of Artificial Intelligence (AI) in the form of deep learning models such as Convolutional Neural Network (CNNs) thus represent a viable solution to enhancing the speed, quality, and accessibility of the diagnosis of skin diseases.

CNNs are designed to automatically and adaptively learn spatial hierarchies of features through backpropagation, making them particularly effective for image classification tasks. Their ability to capture patterns in dermoscopic and clinical images enables the identification of subtle features that may elude the human eye. However, training CNNs from scratch typically requires large, annotated datasets, which are not always available in the medical domain. To address this, Transfer Learning (TL) has emerged as a solution, allowing the reuse of models pretrained on large-scale image datasets such as ImageNet and adapting them for domain-specific tasks like dermatological diagnosis.

The effect of CNNs and TL in combination has resulted in high-powered diagnostic systems used in the classification of skin diseases. These models are promising to discriminate among various skin conditions, and in some instances, they have demonstrated superior performance to that attained by trained dermatologists. Furthermore, the emergence of mobile computing and web applications means that diagnostic support can be implemented in real-time and, as such, become a valid solution, making AI-based technologies a viable tool able to support both community health workers and patients.

This review gives an in-depth analysis of the existing methodologies applied in using CNNs and TL in skin disease identification. It examines the other publicly available dermatological data sets, preprocessing algorithms, model structure, and performance metrics. Besides, the paper also lists the existing issues like model generalizability, explainability, and ethical implications, and presents future research directions that could give future directions in developing effective and implementable diagnostic AI-powered systems. This paper would find it necessary to provide the foundation for developing a web-based app that would support early and correct diagnosis of skin diseases, particularly in low-resource contexts.

A. Skin Diseases and Challenges in Diagnosis

Melanoma, seborrheic keratosis, psoriasis, eczema, and basal cell carcinoma are some common skin illnesses whose manifestations appear visually superimposed, making it hard to diagnose them. Diseases of the skin are of an inflammatory, proliferative, autoimmune nature, or cancerous. The skin color, lighting illumination, and the quality of images tend to obscure their detection. Survival can be dramatically enhanced by an early detection of such malignancies as melanoma. But it may be precisely diagnosed with the help of dermatoscopic imaging and specialist dermatologists, which is less available in rural or underserved areas. This gap could be filled with the help of automated diagnostic systems offering clinical decision support.

B. Image Processing in Dermatology

Raw skin images should be preprocessed using image segmentation, enhancement, and noise removal, as well as contrast operations. The steps aid in enhancing feature extraction and model robustness. The more advanced preprocessing approaches encompass:

- **Illumination correction:** Normalisation of brightness and colour.
- **Lesion border detection:** Enhancing input quality of segmentation algorithms.
- **Color constancy algorithms:** Reducing the lighting-induced color differences.

C. CNNs in Medical Imaging

NNs acquire resolution to spatial hierarchies of features automatically from input. A common CNN structure to classify skin lesions has several convolutional blocks extracting features, pooling layers to downsample the feature space, and fully connected layers to perform the classification. To enhance training dynamics, ReLU activations, dropout, and batch normalization are often employed. CNNs have been applied in both binary and multi-class classification scenarios, e.g., binary classification such as benign vs. malignant, or multi-class classification that may include classifying from one of 7+ skin conditions. CNNs are able to learn high-dimensional patterns directly through image data, thus making them outperform traditional ML models.

D. Transfer Learning

Transfer Learning is an approach that uses already trained models that are trained on massive datasets (such as ImageNet), and after training, the model is refined so that it can solve skin lesion and classification problems. The training is time and computationally cost-reducing and increases the generalization of the model. The well-known pretrained algorithms are:

- **VGGNet:** It has a simple yet deep architecture.
- **ResNet:** Modifies direct connection to allow improvements in gradient flow through more explicit residual connections.
- **DenseNet:** Sharing features through dense connections.
- **EfficientNet**: Scalable architecture to attain state-of-the-art performance using fewer parameters.

II. RELATED WORK

In the presented research article, a new way to classify skin lesions was proposed, which takes advantage of Convolutional Neural Networks (CNNs) and transformer networks, allowing them to classify skin lesions more precisely. This combination of transformers enabled the model to learn local and global features required in detecting the minute changes in the structures of lesions. This combination of deep learning architecture in the study demonstrated a considerable increase in improved classification accuracy over the application of CNNs alone, indicating potential utility in real-time computer-aided diagnosis devices [1].

This research was on Skin Lesion Localization, which aimed to address the need to further improve Skin Lesion Detection using the EfficientNetB0 architecture, together with a Spatial-Aware Attention equipped with Vision Transformer. This model also maintained computational efficiency as well as focusing on the most important sections of the skin image upon classification. Attention mechanism enabled the system to dynamically control its focus on areas with lesions to enhance their accuracy and robustness towards the detection of complex patterns in dermoscopic images [2].

In this paper, a two-stage system was suggested with segmentation of skin lesions to be implemented with a boundary-aware network and classification with a convolution-transformer hybrid model. The segmentation based upon the boundary awareness accurately captured the margins of lesions, which enhanced the quality of extracted features. This increased the capability of the classifier to distinguish between look-alike skin conditions and resulted in to increase in diagnostic accuracy, especially in separating irregular or fuzzy boundaries of the lesions [3].

This research introduced a blend CNN approach together with transfer learning to identify different forms of skin cancer such as melanoma. The transfer learning aspect used pretrained networks, so less labeled data were required and the training did not take a lot of time. The hybrid model recorded good results in binary and multi-classification. It was also shown to be effective in solving the problem of overfitting and enhancing generalization in the small samples of dermatology data [4].

In this research paper, a multi-level ensemble model was created based on triple attention layers and transfer learning that was customized. This ensemble strategy used all predictions in multiple models, and the triple attention mechanism enhanced the feature-selection process based on spatial, channel, and semantic levels. Thanks to that, the system demonstrated robust classification in cases of visually similar classes of lesions, illumination, and skin tone changes, which is a typical problem in clinical datasets [5].

This paper study has used a simple transfer learning framework to classify skin lesions. The study successfully transferred general capabilities of image recognition to the domain of dermatological images with the help of pretrained deep learning models. This has taken much less time and computational cost, as well as having a high level of accuracy. It was concluded that transfer learning is a feasible and scalable method of skin disease detection, especially in a low-resource environment [6].

This paper studies how the DenseNet-121 architecture was fine-tuned to classify skin cancer. The dense connections of DenseNet enabled feature reuse and thus learning efficiency, and avoided the vanishing gradient using deeper networks. The paper demonstrated that the model was able to generate strong classification performance with comparatively lower overfitting, which qualifies it as one of the models of choice to be used in real-time skin screening devices [7].

This paper explores a model proposed as an optimized CNN having architectural enhancements and checkpoint methods to classify cancerous diseases on skin. Not only has it enhanced the accuracy of the classification as compared to another technique, but also saved a lot of training time; it initialized weights in a better way and allowed the flow of gradients accordingly! The findings were that this optimized CNN design was high in detecting malignant and benign lesions, and in performance across varying cases of image origins [8].

This research paper suggests a multi-class classification strategy presented by the AlexNet architecture with the help of a transfer learning concept. This model was an improvement over the traditional binary classification systems since it considered the complexity of the dermatological practice by categorizing several types of skin lesions. The transfer learning methodology offered good generalization even at small training sets, and reported that this will be useful in assisting dermatologists with automated diagnosis on different classes [9].

In this review paper, a complete survey on recent activities on machine learning and deep learning in skin disease classification was provided. It listed the pros and cons of various models, including CNN, ResNet, and transformer-based models. The paper underlined the increased significance of explainable AI and outlined upcoming suggestions, including multimodal data combination and lightweight structures to be used in mobile applications [10].

Table 1: The major contributions of research in the field of AI in skin disease detection.

Author & Year	Full Title and Journal	Method Used	Outcome	Limitation
Kanhegaonkar et al., 2025	Skin lesion classification using CNN and transformer networks for computer-assisted diagnosis, SysCom Conference	CNN + Transformer hybrid	Achieved improved classification accuracy by combining local and global feature extraction	Requires high computational resources for training
Shaheen et al., 2025	Advanced skin lesion detection via EfficientNetB0 and vision transformer with spatial-aware attention, Multimedia Tools Appl.	EfficientNetB0 + Vision Transformer with attention	Enhanced focus on lesion areas with better diagnostic accuracy	Limited evaluation on diverse skin types
Amin et al., 2025	Skin lesion segmentation using boundary-aware network and classification based on convolution transformer mixture, Front. Med.	Boundary-aware segmentation + CNN-Transformer	Precise lesion boundary detection and improved classification	Complexity increases model training time
Mohan Shukla et al., 2024	A hybrid CNN with transfer learning for skin cancer disease detection, Med. Biol. Eng. Comput.	Hybrid CNN + Transfer Learning	Improved generalization and reduced overfitting	Performance depends on quality of pretrained weights
Hossain et al., 2024	A multi-level ensemble approach for skin lesion classification using TL	Ensemble learning + Triple Attention + TL	Strong classification in multi-class tasks	High memory usage and long training time

III. Datasets for Skin Disease Detection

A. Datasets

These datasets are of different quality, resolution, class distribution, and accuracy of annotation. Most models are trained using these datasets, as both appear to be well accepted and have a standard format (HAM10000 and ISIC datasets). Nonetheless, obstacles such as the imbalance of classes and artifacts of the images overlap.

Table 2: Datasets for Skin Disease Detection

Dataset	**Image Count**	**Disease Classes**	**Type**	**Source**
HAM10000	10,015	7	Dermoscopic	ISIC Archive
ISIC 2019	25,331	8	Dermoscopic	ISIC Challenge
Derm7pt	~2,000	7	Clinical	ISIC Archive
PH2	200	3	Dermoscopic	Univ. of Porto

B. Preprocessing Techniques

Preprocessing is essential because the quality of input information can influence the model performance in a major way, particularly in medical imaging, where the lesions in question are frequently lowly obvious and tiny.

- **Artifact Removal:** DullRazor, median filter, or morphological operations are used to remove hairs and the shadows.
- **Image Augmentation:** Artificial increases in the number of training samples are achieved by random flipping, cropping, rotation, zooming, as well as brightness modulation that provides a strengthening of the model.
- **Color Normalization:** Converting RGB Maybe to HSV, LAB, or YCbCr color begins by boosting the lesion contrast and facilitating invariance of color.
- **Segmentation:** Focusing the classification on the region of interest (ROI) based on models such as U-Net, Mask R-CNN, or thresholding-based techniques significantly reduces noise and improves the focus of the classification.

C. Custom CNN Models Architectures

The custom architectures are built from the ground up and customized to certain sorts of characteristics in the dataset. These are frequently implemented with lower layers, concretely optimized hyperparameters, and less complex setups suitable for research with limited computing power.

- Pros: They are optimized to perform a certain job, less intensive in computation
- Cons: Low tolerance to small datasets, Demands close attention to the hyperparameter tuning

D. Pretrained Models

The popularity of these pretrained models is based on their accuracy in real-world uses and availability of pre-trained weights. Fine-tuning is usually done to retrain the last few layers and freeze the other earlier layers.

Table 3: Pretrained Models (Transfer Learning)

Model	**Accuracy Range**	**Strengths**	**Limitations**
VGG16/VGG19	82%–85%	Easy to fine-tune, deep layers	High memory usage
ResNet50	86%–90%	Skip connections solve vanishing gradients	Larger size
MobileNetV2	85%–88%	Lightweight, mobile-ready	Slightly less accurate
DenseNet121	88%–92%	Feature reuse, efficient learning	Slower training
EfficientNet	90%–94%	Compound scaling, state-of-the-art	Complex to configure

Model performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). AUC is especially important in imbalanced datasets as it provides a balanced measure of sensitivity and specificity.

Table 3: Performance Comparison

Study	**Dataset**	**Model**	**Accuracy**	**AUC**	**Notable Findings**
Abbas et al. (2025)	HAM10000	ResNet50	91.2%	0.93	Balanced performance
Gupta et al. (2024)	ISIC 2019	MobileNetV2	88.5%	0.90	Fast inference, low memory
Khan et al. (2023)	HAM10000	DenseNet121	92.1%	0.94	Best accuracy, better generalization
Proposed (Future Work)	HAM10000	TL + Web App	TBD	TBD	Web-based AI integration planned
Study	Dataset	Model	Accuracy	AUC	Notable Findings

IV. Challenges and Limitations

The challenges and limitations of a model development of robust skin disease detection and clinically useful systems are listed as follows:

- **Unbalanced Datasets:** The models can be biased by the over-representation of benign lesions and the under-representation of malignant cases.
- **Generalization Problems:** The training on a particular dataset cannot result in good performance on other datasets because of varying demographics and image quality.
- **Explainability:** Interpretability is not possible, which limits the trust and application in clinical practice.
- **Absence of Data Privacy:** Sharing sensitive information about patients poses some legal and ethical concerns.
- **The Deployment Barriers:** Deployment of models on edge devices is limited by the amount of power, large model size, and high computational cost.

V. Future Research Directions:

The major future research trend is to eliminate the existing limitations and further develop AI-based skin disease detection research as follows:

- **Explainable AI (XAI):** Methods, such as Grad-CAM and LIME, give visual representations, which increase the credibility of the forecasts.
- **Hybrid Architectures:** Adding CNNs together with the attention mechanism or transformers to improve the contextual or spatial awareness.
- **Multi-Modal Fusion:** The integration of text (history of the patient, his symptoms) with image data to make more sensible decisions.
- **Cloud-Based and Edge Applications:** Using the cloud as the training platform and edge devices on which to run inference to provide scalable applications.
- **Federated Learning:** Learning a joint model on several decentralized devices or institutions without revealing raw data.
- Self-Supervised Learning: Using data that is not labeled, through which we can minimize the use of costly labeled datasets.

VI. Conclusion

Combining Convolutional Neural Networks (CNNs) and Transfer Learning (TL) has been pivotal in the evolution of the profession of skin disease diagnosis through automated methods, which also presents a real possibility to replace more labor-intensive methods of diagnosis. This review has pointed to the fact that TL-enhanced CNN architectures like DenseNet, EfficientNet, and ResNet can be reasonably used to display a high level of accuracy and robustness in various datasets. These AI-driven systems could facilitate timely and effective diagnosis due to the use of dermoscopic images and clinical images in areas where dermatologists are not accessible, either due to a lack of professionals or other factors. Nonetheless, there are still some obstacles to clinical implementation, such as model generalization between populations, privacy issues regarding patient data, and AI systems' interpretability that is likely to be trusted by healthcare providers. Such concerns need to be resolved with explainable AI, decentralized learning, and lightweight model deployment on web and mobile devices to become useful.

This review has not only resynthesized the status of research so far but also forms the basis through which the same application can be developed through a web-based application in the future using CNN and TL to screen skin disease. As the area of AI innovations is further developed and collaborative work between AI scholars and dermatologists continues, these systems will have the power to disrupt the approach to skin healthcare by rendering early detection more available, precise, and globally scalable.

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