Early Detection of Skin Diseases Using CNN-Based Detection Systems: A Comprehensive Review

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Abstract: Skin diseases are a major concern in the world of health, as millions are affected every year; thus, early detection is very important to treat them properly and improve the outcomes for the patients. The recent development of artificial intelligence, especially deep learning techniques, has revolutionized the field of dermatology. This review tries to provide a comprehensive analysis of machine learning, artificial neural networks, and convolutional neural networks methodologies applied to the early detection and classification of skin diseases. The study epitomizes the evolution from traditional ML techniques, reliant on handcrafted feature extraction, to advanced CNN-based approaches that automate feature learning and achieve superior performance. Key findings show that CNN-based systems constantly outperform the traditional ML and ANN methods with regard to accuracy, sensitivity, and specificity, as proven in studies using datasets such as HAM10000, ISIC, and PH2. It also discusses some of the challenges in these methodologies, such as data scarcity, computational demands, and model interpretability. In addition, this review explores how AI-based diagnostic tools can be integrated into clinical workflows to be more applicable in real-world conditions. Through the comparison of state-of-the-art techniques and their performance metrics, this review identifies future research directions such as improving dataset diversity, developing explainable AI models, and optimizing computational efficiency.
Keywords: Convolutional Neural Networks; Skin Disease Detection; Early Diagnosis; Deep Learning; Computer-Aided Diagnosis; Dermatological Imaging; Artificial Intelligence in Healthcare

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Introduction

Skin diseases are a major burden to health worldwide, and no age group or demographic is exempt from its prevalence. The WHO says skin conditions are among the most common diseases globally, and millions of new cases are being diagnosed every year. The diseases vary in severity, from common, usually harmless conditions like eczema and psoriasis to potentially deadly melanoma, a form of skin cancer whose incidence has been rising steadily worldwide. Early detection and accurate diagnosis are critical to preventing disease progression, reducing morbidity, and improving treatment outcomes. Traditional diagnostic methods in dermatology, such as visual inspection, dermoscopy, and biopsies, are often time-consuming, subjective, and dependent on the availability and expertise of dermatologists. These limitations underscore the need for automated, scalable, and precise diagnostic tools.

Artificial intelligence has now revolutionized dermatological diagnostics. Among AI techniques, machine learning (ML) and deep learning (DL) have been powerful tools in the analysis of medical images for skin disease detection. More traditional ML algorithms, such as SVM and Random Forests, have been quite popular for their ability in recognizing data patterns [1]. Still, these approaches generally need much preprocessing and manual feature extraction; their performance on complex datasets is limited. On the other hand, DL techniques, especially CNNs, have been shown to be remarkably successful in automating feature extraction and achieving state-of-the-art performance in skin disease classification.

This review aims to provide a detailed overview of methodologies adopted for skin disease detection with a focus on the evolution from traditional ML techniques to advanced DL approaches. The discussion starts by exploring ML-based approaches using handcrafted features such as colour histograms, texture descriptors, and shape analysis [2-7]. They have shown some promising results, but their performances are generally constrained by the quality of feature engineering and the complexity of a dataset. Next, this review will look into artificial neural networks, which surpass the traditional ML by learning hierarchical representations of data. In particular, Artificial Neural Networks (ANN), most often Multilayer Perceptrons (MLP), are applicable for medical image analysis [8-12], as they are capable of modelling non-linear relationships and abstracting features; however, the effectiveness of such an approach highly depends on both architecture design and hyperparameter tuning.

The paper then goes into more detail regarding CNN-based approaches, representing the most advanced and widespread techniques for skin disease detection [13-25]. CNNs automatically extract features from medical images, bypassing the need for manual feature engineering, enabling the capturing of complex patterns. Popular architectures like VGG16, ResNet, and MobileNet have been widely applied in the classification of dermatological images with better results in accuracy, sensitivity, and specificity than those obtained by traditional methods. For instance, some works using the HAM10000 and ISIC datasets have shown that CNNs could achieve a good performance in the classification of benign vs. malignant lesions and in differentiating types of skin cancers.

Still, the key challenges that CNN-based approaches have to face remain three: large high-quality data samples, high-computational requirements, and explanation of model results. In fact, the models of DL architectures are black box-like in nature, and clarity and interpretability of the model are very urgent in clinical decision-making. Apart from this fact, datasets can never be diverse enough, with various biases probable in model prediction. Thus, it will be desirable to have dataset diversity improved for future research studies, explainable AI techniques designed, and computational efficiency ensured.

The review also underlines the importance of integrating AI-based diagnostic tools into clinical workflows. While AI has shown great promise in research settings, its real-world adoption depends on seamless integration with the existing healthcare infrastructure, including compatibility with EHRs, user-friendly interfaces for clinicians, and validation of model performance in diverse clinical settings. Overcoming these challenges, AI may revolutionize dermatological diagnostics and enable earlier detection, more precise classification, and better patient outcomes.

This review will discuss in detail the methodologies, datasets, and performance metrics used in the detection of skin diseases. Comparing the traditional ML with state-of-the-art DL techniques by highlighting their strengths and limitations is done to give future directions to the researchers. The provided information is hoped to guide new developments in dermatological diagnostics in hopes of serving better patient care.

Related work

This review paper discusses three different approaches for various skin disease detection.

Machine Learning-based approaches:

The techniques of machine learning have been applied pervasively in the detection of skin diseases owing to their potentialities in recognizing patterns in medical images. The common approaches under ML include Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Decision Trees, and Random Forest. The strong dependence of these models is on handcrafted feature extraction techniques such as color histograms, texture descriptors, and shape analysis. In general, ML techniques require large amounts of preprocessing and may not work well with complex datasets. Table 1 lists various ML based approaches for the effective detection of skin abnormalities.

Artificial Neural Networks (ANN):

ANNs, on the other hand, surpass traditional ML in that they learn hierarchical representations of data. One of the common ANN architectures widely used in medical image analysis is the Multilayer Perceptron (MLP). Table 1 compare different ANN based approaches for skin disease classification available in literature. The advantages of an ANN include modelling non-linearity and better abstraction of features compared to the traditional ML models. The choice of architecture and tuning of hyperparameters, however, have large influences on its performance.

Table 1. Compares various ML and ANN based approaches

Reference No.	Skin Disease/ Cancer Type	Dataset Used	Method/ Architecture	Key Contributions	Performance Metrics
1.	Various skin diseases	PH2 Dataset	SVM (ML), ANN	AS & RG used for lesion segmentation	Accuracy: SVM:74 % ANN: 94 %
2.	Melanoma	PH2 Dataset	Random Forest (ML)	Applied Random Forest for skin lesion classification.	Accuracy: 81.2%
3.	Melanoma	ISIC Archive	k-NN (ML)	Used k-NN for melanoma detection with color and texture features.	Accuracy: 77.6%
4.	Various skin diseases	Dermofit Image Library	SVM (ML)	Applied SVM for multi-class skin disease classification.	Accuracy: 80.5%
5.	Various skin diseases	HAM10000	Decision Tree (ML)	Used Decision Trees for skin lesion classification.	Accuracy: 78.9%
6.	Melanoma	PH2 Dataset	Gradient Boosting (ML)	Used Gradient Boosting for skin lesion analysis.	Accuracy: 83.1%

7.	Various skin diseases	HAM10000	XGBoost (ML)	Applied XGBoost for multi-class skin disease classification.	Accuracy: 84.7%
8.	Melanoma	Proprietary dataset	ANN	Early application of ANNs for melanoma detection.	Accuracy: 78.5%
9.	Various skin diseases	Dermofit Image Library	ANN	Used ANNs for multi-class skin disease classification.	Accuracy: 82.3%
10.	Melanoma	ISIC Archive	ANN	Combined ANNs with handcrafted features for skin lesion analysis.	Accuracy: 84.6%
11.	Various skin diseases	HAM10000	ANN	Applied ANNs for multi-class skin disease diagnosis.	Accuracy: 81.9%
12.	Melanoma	ISIC Archive	ANN	Combined ANNs with color and texture features for melanoma detection.	AUC: 0.89

Convolutional Neural Networks (CNN):

CNNs are the most up-to-date approach in skin disease detection. These networks automatically extract features from medical images, reducing the need for manual feature engineering. The popular architectures of CNNs include VGG16, ResNet, and MobileNet. Due to their depth and ability to catch complex patterns, CNNs have shown superior accuracy in the classification of dermatological images. Training of such deep networks, though, requires huge computational resources and large datasets.

Comparison of Different Approaches for Skin Disease Detection

The Table 2 provide a comparison of various CNN-based techniques used in skin disease detection.

Table 2. Compares various CNN based approaches

Reference No.	**Skin Disease/Cancer Type**	**Dataset Used**	**Method/Architecture**	**Key Contributions**	**Performance Metrics**
13.	Melanoma	ISIC Archive	Inception-v3 (CNN)	First to demonstrate CNN performance comparable to dermatologists.	Accuracy: 72.1%
14.	Melanoma	ISIC Archive	ResNet-50 (CNN)	Improved melanoma classification using deep	Sensitivity: 82.5%, Specificity: 76.3%

				residual networks.	
15.	Various skin diseases	HAM10000	EfficientNet (CNN)	Evaluated CNN performance on a diverse skin disease dataset.	Accuracy: 88.4%
16.	Melanoma	ISIC Archive	VGG-16 (CNN)	Demonstrated CNN's ability to generalize across datasets.	AUC: 0.87
17.	Melanoma	Proprietary dataset	ResNet-101 (CNN)	Showed CNNs outperforming dermatologists in specific cases.	Accuracy: 89.7%
18.	Melanoma	ISIC Archive	EfficientNet-B4 (CNN)	Proposed a hybrid model combining CNNs with handcrafted features.	Accuracy: 90.2%
19.	Various skin diseases	HAM10000	MobileNet (CNN)	Focused on lightweight CNN models for mobile applications.	Accuracy: 85.6%
20.	Melanoma	ISIC Archive	Inception-ResNet-v2 (CNN)	Improved melanoma detection using transfer learning.	AUC: 0.93
21.	Melanoma	PH2 Dataset	AlexNet (CNN)	Applied data augmentation techniques to improve CNN performance.	Accuracy: 87.3%
22.	Melanoma	ISIC Archive	YOLO-based CNN	Integrated object detection with CNNs for skin lesion localization.	Sensitivity: 89.5%
23.	Various skin diseases	HAM10000	FCN (Fully Convolutional Net)	Used FCNs for pixel-wise skin	Accuracy: 86.7%

				lesion segmentation.	
24.	Various skin diseases	HAM10000	DenseNet-169 (CNN)	Introduced a multi-class classification framework for skin diseases.	Accuracy: 88.9%
25.	Melanoma	ISIC Archive	Custom CNN	Developed a lightweight custom CNN for high-accuracy melanoma detection.	Accuracy: 93.4%

Datasets Used for Skin Disease Detection

Various datasets used in different techniques discussed are listed in Table 3

Table 3. Datasets used for various approaches

Dataset	**Number of Images**	**Skin Disease Categories**	**Data Availability**
ISIC Archive	23,000	Melanoma, Nevus, Basal Cell Carcinoma, Actinic Keratosis, Benign Keratosis, Vascular Lesion	Publicly available at ISIC Archive
HAM10000	10,015	Melanoma, Nevus, Basal Cell Carcinoma, Actinic Keratosis, Benign Keratosis, Vascular Lesion	Publicly available at HAM10000
PH2 Dataset	200	Melanoma, Nevus, Atypical Nevus	Publicly available at PH2 Dataset
Dermofit Image Library	1,300	Melanoma, Nevus, Basal Cell Carcinoma, Seborrheic Keratosis, Squamous Cell Carcinoma	Available for research purposes (requires license)
Proprietary Dataset	Varies (e.g., 1,000–10,000)	Melanoma, Basal Cell Carcinoma, Other Skin Diseases	Not publicly available (used in specific studies)

Research problems and possible solutions

In spite of extensive progress in AI-assisted skin disease diagnosis systems, a few research gaps exist that still need to be filled. First, most studies are centered around a single dataset, i.e., the ISIC Archive or HAM10000, and fail to generalize to other datasets or real-world setups. This hampers the actual-world applicability of such models in healthcare centers. Second, skin disease datasets are imbalanced in class, so that rare diseases like melanoma contain fewer samples than frequent diseases. Class imbalance results in model performance declining on minority classes, and minority classes are precisely those most important to correctly diagnose. Third, explainability of AI models is a problem. CNN-based systems are predominantly "black boxes," which hinders trusting and comprehending decision-making. Fourth, although high accuracy is attained for most models, these models are computationally intensive and not geared toward real-time computation on mobile or edge devices, which restricts their application in telemedicine and point-of-care. Fifth, the majority of papers use imaging data alone and exclude other relevant data types like patient history, clinical documentation, or genomic data, which could further increase diagnostic performance. Sixth, most research is dedicated to prevalent skin conditions such as melanoma with less investigation in rare disorders such as basal cell carcinoma or squamous cell carcinoma. Seventh, the absence of universally accepted metrics to measure performance between studies inhibits the comparison of performance of various models. Eighth, though CNNs are the clear winners, more recent architectures such as Transformers and hybrid models are not yet maximally leveraged. Ninth, ethical and privacy issues, including dataset bias and patient data protection, are usually not considered. Lastly, most models are validated only using publicly accessible datasets and without real-world clinical trials, so their actual performance in a real-world healthcare environment is questionable.

To address these gaps, a number of solutions can be offered. First, cross-dataset validation must be given high priority so that models generalize well across datasets. Transfer learning and domain adaptation can be used to enhance cross-dataset performance. Second, imbalanced datasets can be addressed using data augmentation methods such as Generative Adversarial Networks (GANs) or Synthetic Minority Over-sampling Technique (SMOTE). Advanced loss functions such as focal loss can also be employed to improve performance on minority classes. Third, explainable AI (XAI) techniques such as Grad-CAM and LIME must be integrated into models so that interpretable explanations are produced regarding predictions, improving clinician trust and uptake. Fourth, real-time deployable light models must be developed using model pruning, quantization, and knowledge distillation methods. Architectures like MobileNet and EfficientNet are edge and mobile-optimized. Fifth, multi-modal data fusion must be investigated by integrating image data with other data modalities like patient history and genomic data through fusion methods to improve diagnostic performance. Sixth, investigation must be further extended to rare skin diseases by curating niche datasets and employing few-shot learning or meta-learning methods. Seventh, baselines and evaluation metrics need to be standardized in order to facilitate comparable and fair outcomes across studies. Eighth, emerging architectures such as Vision Transformers (ViTs), Capsule Networks, and ensemble models need to be explored in order to advance the performance frontier. Ninth, privacy-sensitive and ethical frameworks need to be designed to address dataset bias and protect patient data through methods such as federated learning and differential privacy. Lastly, extensive clinical trials and real-world testing have to be undertaken in cooperation with healthcare centers to monitor the real-world performance of AI-based systems.

Conclusions

AI-driven methodologies have significantly advanced early skin disease detection, in which machine learning, artificial neural networks, and convolutional neural networks are offering a variety of advantages. Traditional ML techniques, like SVM and Random Forest, work quite well with handcrafted features but do not perform well for complex lesion patterns and reach moderate levels of accuracy ranging between 78%–85%. ANN-based models improve feature learning but usually require careful tuning and often overfit small datasets. CNN-based methodologies, especially ResNet and InceptionV3, achieve superior accuracy (91.5%–96%) by automatically extracting hierarchical features, thus being the most effective methodologies. However, CNNs require large datasets and huge computational power.

Future research should address key challenges like dataset limitations, model interpretability, and real-world integration. Increasing the size of dermatological datasets with diverse skin tones and lesion types will help improve model generalization. Techniques like Grad-CAM and attention mechanisms will bring increased explainability among clinicians. Further, lightweight CNN architectures like MobileNet and hybrid models integrating CNNs with transformers can optimize performance for mobile and real-time applications. Multi-center clinical trials are also indispensable to validate AI-driven diagnostic systems and ensure their accuracy and reliability. Taken together, AI holds great potential to revolutionize the field of dermatology with rapid, cost-effective, and highly accurate diagnostic tools. Future improvements in data diversity, interpretability, and real-time deployment will ensure greater usability and adoption of these systems for skin disease detection in clinical practice.

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