INTERNATIONAL JOURNAL OF ADVANCED INNOVATIVE TECHNOLOGY IN ENGINEERING

Published by Global Advanced Research Publication House Journal

Home page: www.ijaite.co.in

A Comprehensive Review of Skin Disease Detection and Classification Using Machine Learning and Deep Learning Techniques

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Article History

Received on: 17 April 2025

Revised on: 27 April 2025

Accepted on: 02 May 2025

Keywords: Skin Diseases, Artificial Intelligence, automated Detection, Machine Learning, Deep Learning

e-ISSN: 2455-6491

DOI: 10.5281/zenodo.15332460

Production and hosted by
www.garph.org

ABSTRACT

Skin diseases are among the most common health concerns worldwide, with timely and accurate diagnosis playing a critical role in effective treatment and patient outcomes. Recent advancements in Artificial Intelligence, particularly in Machine Learning and Deep Learning have shown immense promise in the automated detection and classification of skin conditions. This review provides a comprehensive analysis of existing ML and DL techniques used for skin disease diagnosis, covering classical algorithms such as Support Vector Machines, k-Nearest Neighbors, and Random Forests, as well as state-of-the-art Convolutional Neural Networks, including ResNet, VGG, Inception, and DenseNet. We also explore the role of transfer learning, attention mechanisms, and ensemble models in enhancing diagnostic performance. Moreover, we discuss current challenges including data scarcity, generalization, interpretability, and ethical concerns. Real-world applications such as mobile diagnostic apps, telemedicine integration, and deployment in remote healthcare settings are also examined. This review concludes by underscoring the transformative potential of AI in dermatology and calls for stronger interdisciplinary collaboration between clinicians and data scientists to develop robust, ethical, and scalable diagnostic systems.

1. INTRODUCTION

The skin, the body's largest organ, serves as the first line of defense against environmental threats. However, it is vulnerable to a wide range of conditions triggered by bacterial and fungal infections, viral agents, and allergic reactions [1]. Among these, skin lesions are among the most frequently encountered issues globally. While lesions often appear as abnormal changes in skin texture or color, accurate diagnosis remains challenging due to symptom overlap across different types of skin conditions. For example, both contact dermatitis and eczema exhibit similar visual symptoms such as redness, swelling, and cracked skin, measles and keratosis may both present with sporadically scattered red spots, complicating visual differentiation. These visual similarities can lead to misdiagnoses, especially by dermatologists with limited clinical experience.

Timely and accurate diagnosis of skin lesions is critical, as early detection often leads to better treatment outcomes and increased recovery rates. Nevertheless, training a skilled dermatologist is a long and costly process. In 2024, the average cost of medical education in the United States reached approximately USD 358,192, with tuition fees increasing annually since 2016 [2]. The need for an efficient, automated diagnostic system is thus more pressing, particularly in low-resource regions that often face shortages in medical infrastructure and trained professionals.

Over the past decade, artificial intelligence (AI) has made remarkable advancements in image analysis, driven by the integration of machine learning (ML) and deep learning (DL) techniques. These technologies enable the development of robust models for segmentation and classification of medical images. While traditional ML approaches rely on manual feature extraction and simpler architectures, DL models autonomously learn hierarchical and discriminative features from raw image data [4]. This capability has sparked considerable interest in applying AI for medical diagnostics, especially in dermatology. In fact, DL-based systems have already achieved diagnostic performance comparable to dermatologists with up to five years of experience [5], positioning DL as a promising and cost-effective solution for skin disease detection.

The success of AI in healthcare applications depends heavily on access to large, well-annotated datasets to ensure both reliability and generalization. To accelerate progress in this field, collaborative efforts have led to the creation of benchmark datasets such as the International Skin Imaging Collaboration (ISIC), which hosted annual challenges from 2016 to 2020 to drive innovation in skin disease diagnosis [6]. A major focus of this research is melanoma detection—a critical task, given its high mortality rate. According to the World Health Organization (WHO), melanoma cases are projected to reach 466,914 by 2040, with an estimated 105,904 related deaths [7].

In recent years, numerous publicly available datasets containing macroscopic and dermoscopic images have become accessible online, playing a crucial role in advancing skin disease detection research. Notable examples include the PH2 dataset [8], the HAM10000 (Human Against Machine with 10,000 training images) dataset [9], the BCN 20000 dataset [10], the EDRA Interactive Atlas of Dermoscopy dataset [11], and the Med-Node dataset [12]. Depending on the specific research objectives, these datasets can be used independently, in part, or in combination. Macroscopic images—often captured using conventional digital or smartphone cameras—depict external views of skin lesions, while dermoscopic images, obtained through standardized clinical procedures, reveal subsurface skin structures with fewer artifacts and enhanced detail. Dermoscopic imaging, by exposing features not visible to the naked eye, typically provides more reliable input for segmentation and classification tasks compared to macroscopic imaging [13], despite potential variations in lighting, resolution, or image capture distance.

To ensure a comprehensive and systematic overview of the current progress in skin lesion detection, we employed a targeted literature search strategy using PubMed, a widely respected repository for biomedical and life sciences research. Our review emphasizes studies published from 2023 onward that explore machine learning-based solutions for skin lesion classification and diagnosis. In conducting this review, we also utilized high-quality datasets curated by medical and academic institutions. These resources have not only facilitated the development and evaluation of diagnostic algorithms but also contributed to public awareness about the significance of early detection and skin health education. Through the analysis of these datasets and the associated research studies, we aim to present the current landscape of AI-driven dermatological diagnostics while identifying research gaps and opportunities for future innovation.

2. MACHINE LEARNING TECHNIQUES FOR SKIN DISEASE DETECTION

ML techniques have played a foundational role in the development of automated systems for skin disease detection and classification. Traditional ML models rely on handcrafted features extracted from skin images and use these features to train classifiers capable of distinguishing between various skin conditions [14]. This section outlines the core components of traditional ML approaches, including common classifiers, feature extraction strategies, and preprocessing methods, followed by a discussion on their benefits and limitations.

A. Traditional Machine Learning Models

Several classical ML algorithms have been widely applied in dermatological image analysis:

Support Vector Machine (SVM): SVMs are effective for high-dimensional feature spaces and are particularly useful in binary classification tasks. Their use in skin disease detection includes separating benign from malignant lesions based on extracted features.

K-Nearest Neighbors (KNN): A non-parametric algorithm that classifies a sample based on the majority vote of its ‘k’ nearest neighbors. Though simple to implement, KNN can be computationally intensive for large datasets.

Random Forest (RF): An ensemble learning method that constructs multiple decision trees and combines their predictions. It is robust to overfitting and can handle imbalanced datasets effectively.

Naïve Bayes (NB): A probabilistic classifier based on Bayes’ theorem, assuming independence between features. It performs well with smaller datasets and is computationally efficient.

B. Feature Extraction Techniques

Traditional ML relies heavily on the manual extraction of discriminative features from input images. Common feature types include:

Color Features: Histograms, color moments, and color constancy models help capture lesion pigmentation, which is often a strong indicator of disease type.
Texture Features: Techniques such as Local Binary Patterns (LBP), Gabor filters, and Gray Level Co-occurrence Matrix (GLCM) extract texture patterns that help in differentiating skin abnormalities.
Shape Features: Contour-based descriptors, area, perimeter, symmetry, and border irregularity are extracted to assess lesion morphology, which is crucial for melanoma identification.

C. Preprocessing and Segmentation Techniques

Preprocessing enhances image quality and removes artifacts like hair, shadows, and background noise. Common preprocessing steps include:

Image Normalization: Standardizes pixel values to ensure consistency in brightness and contrast.
Hair Removal: Algorithms like DullRazor are used to eliminate hair artifacts that may interfere with feature extraction.
Noise Reduction: Median and Gaussian filters are employed to smooth images and suppress unwanted noise.

Segmentation techniques are used to isolate the lesion from surrounding healthy skin. Popular segmentation approaches include:

Thresholding: Separates lesion and background using pixel intensity thresholds.
Edge Detection: Detects boundaries using operators like Sobel or Canny.
Region-Based Methods: Includes region growing and watershed algorithms that group pixels with similar characteristics.

D. Advantages and Limitations of Classical ML Approaches

Advantages:

- Require less computational power compared to deep learning models.
- Easier to interpret and debug.
- Work effectively with smaller datasets.
- Faster training times and lower resource requirements.

Limitations:

- Performance heavily depends on the quality of manually extracted features.
- Limited ability to generalize to complex and high-dimensional image data.
- Poor scalability for large datasets or multi-class classification tasks.
- Feature engineering requires domain expertise and can be time-consuming.

3. DEEP LEARNING APPROACHES FOR SKIN DISEASE DETECTION

DL has revolutionized image-based medical diagnostics by enabling end-to-end learning systems that automatically extract complex, hierarchical features from raw input images. Convolutional Neural Networks (CNNs), in particular, have demonstrated remarkable success in various skin disease detection tasks, including classification, segmentation, and lesion localization [15]. This section outlines the core DL architectures, advanced techniques, and recent innovations applied in dermatological image analysis.

A. CNN-Based Architectures

CNNs have become the backbone of skin image classification and segmentation due to their ability to learn spatial hierarchies of features.

VGGNet: Known for its simplicity and depth, VGG uses small convolutional filters (3×3) and uniform architecture. Despite its high accuracy, it is computationally expensive due to a large number of parameters.
ResNet (Residual Network): ResNet addresses the vanishing gradient problem in deep networks by introducing residual connections. Its deeper layers allow for improved feature learning and are commonly used in medical image classification.
Inception Network: This model employs parallel convolutions of different sizes in a single layer, allowing for multi-scale feature extraction. Inception's modular design reduces computational cost while preserving accuracy.
DenseNet: Dense Convolutional Networks connect each layer to every other layer, enhancing feature reuse and reducing the number of parameters. This dense connectivity makes DenseNet highly effective for subtle pattern recognition in dermoscopic images.

B. Transfer Learning and Fine-Tuning

Transfer learning has become a popular strategy in medical imaging where annotated data is limited. In this approach, models pre-trained on large-scale datasets like ImageNet are fine-tuned on domain-specific data such as dermoscopic images [16]. This significantly reduces training time and improves generalization.

Fine-tuning allows model weights to adapt to the target task by updating selected layers, typically the final classification layers, while earlier layers retain the learned low-level features from pretraining.

C. Attention Mechanisms and U-Net for Segmentation

Attention Mechanisms: Attention modules enhance model performance by enabling it to focus on the most relevant parts of the image, such as lesion regions [17]. They have been incorporated into CNNs to improve lesion localization and classification accuracy.

U-Net: U-Net is a widely used encoder-decoder architecture for biomedical image segmentation. It uses skip connections to combine semantic and spatial information from different layers, making it highly effective in delineating lesion boundaries with precision [18].

Advanced variations like Attention U-Net, UNet++ and DeepLab have further improved segmentation accuracy in skin lesion tasks.

D. Ensemble Learning in Deep Learning

Ensemble learning combines predictions from multiple models to improve robustness and performance. In deep learning, this can involve:

- Averaging or voting across different CNN architectures.
- Combining different model checkpoints.
- Using stacking or boosting techniques.

Ensemble methods help mitigate model bias and variance, resulting in more reliable predictions in clinical scenarios. For instance, combining ResNet and DenseNet has shown improved diagnostic accuracy for melanoma detection.

E. Recent Advances: Vision Transformers and Hybrid Models

Vision Transformers (ViTs): Unlike CNNs, ViTs treat images as sequences of patches and apply self-attention mechanisms to model global relationships. Recent studies show that ViTs achieve competitive or superior performance compared to CNNs, especially when trained on large datasets.

Hybrid CNN-Transformer Models: These models combine the local feature extraction capabilities of CNNs with the global context awareness of Transformers. This hybrid design has shown promise in improving classification accuracy for complex dermatological cases.

Self-Supervised and Semi-Supervised Learning: These techniques are gaining traction for utilizing unlabeled data more effectively, which is particularly useful in medical domains where labeled data is scarce.

Deep learning continues to push the boundaries of automated skin disease diagnosis, offering high accuracy and clinical relevance. The integration of advanced architectures, transfer learning, attention mechanisms, and ensemble strategies ensures that DL models are well-equipped to handle the variability and complexity of dermatological conditions.

4. COMPARATIVE ANALYSIS

The performance of skin disease detection models has significantly improved with the transition from traditional ML methods to DL techniques. This section provides a comparative analysis of both approaches, evaluates them using standard performance metrics, and discusses their strengths and limitations in real-world applications.

A. Performance Comparison: ML vs. DL

Traditional ML algorithms such as SVM, KNN, RF, and NB rely heavily on handcrafted features extracted using domain knowledge. These features often include color histograms, texture descriptors, and shape-based metrics.

In contrast, DL models like CNNs (ResNet, DenseNet, VGG) automatically learn hierarchical and abstract representations from raw images, making them more adept at capturing complex patterns and variations in dermatological images [19].

Table 1: Comparative Analysis of Existing Methods

Approach	Accuracy	Precision	Recall	F1-Score	AUC-ROC
SVM (with handcrafted features)	80–85%	78–83%	77–85%	77–84%	0.82–0.86
Random Forest	82–86%	80–85%	79–87%	79–86%	0.83–0.87
CNN (e.g., VGG, ResNet)	88–94%	86–92%	85–93%	86–93%	0.92–0.96
Ensemble CNN Models	91–96%	90–95%	89–96%	90–95%	0.94–0.98
Vision Transformers	92–97%	91–96%	90–96%	91–96%	0.95–0.99

Table 1 shows the results highlight that DL approaches consistently outperform traditional ML models, particularly in terms of sensitivity (recall) and AUC-ROC—crucial metrics for medical diagnostics where false negatives can be life-threatening.

B. Evaluation Metrics Used

To assess the performance of models across various datasets and tasks, the following standard metrics are commonly used:

Accuracy: Proportion of correctly classified samples.

Precision: Proportion of true positive predictions among all positive predictions.

Recall (Sensitivity): Proportion of actual positives correctly identified.

F1-Score: Harmonic mean of precision and recall, providing a balance between the two.

AUC-ROC (Area Under the Receiver Operating Characteristic Curve): Measures the model's ability to discriminate between classes, particularly useful in imbalanced datasets.

Table 2: Strength and Limitation of Existing Methods

Method	Strengths	Limitations
Traditional ML	- Simpler and faster to train- Works well with small datasets- Easier to interpret	- Requires extensive feature engineering- Limited generalization for complex patterns- Lower accuracy on high-variance images
Deep Learning	- Automatically extracts features- High accuracy on complex and diverse datasets- Scalable and adaptable with transfer learning	- Requires large annotated datasets- Computationally intensive- Less interpretable (“black-box” nature)
Ensemble DL Models	- Improved robustness and accuracy- Reduces bias/variance	- Higher computational cost- Complex to implement and tune
Vision Transformers	- Captures long-range dependencies- Promising for segmentation/classification tasks	- Requires large-scale pretraining- Still emerging in clinical deployment

5. CHALLENGES AND LIMITATIONS

Despite the significant advancements in ML and DL for skin disease detection, several challenges and limitations remain. These issues must be addressed to ensure reliable, interpretable, and clinically deployable AI-based solutions in dermatology.

A. Data Scarcity and Class Imbalance

One of the major hurdles in training robust ML/DL models is the limited availability of high-quality annotated dermatological datasets. Skin disease datasets often exhibit:

- Class imbalance, where common skin conditions like acne or eczema dominate, while rare diseases like melanoma or psoriasis are underrepresented.
- Annotation bottlenecks, since labeling requires dermatological expertise, making the annotation process time-consuming and costly.

This scarcity and imbalance can lead to biased models that perform poorly on rare but clinically critical conditions, increasing the risk of misdiagnosis.

B. Generalization and Overfitting

`Models trained on specific datasets may fail to generalize across diverse patient populations due to:

- Variations in skin tone, lighting, image quality, and device types.
- Differences in data collection protocols across hospitals or regions.

Overfitting is another concern, especially when deep models memorize training data instead of learning generalizable features. This reduces their effectiveness when deployed in real-world settings.

C. Computational Cost and Interpretability

Deep learning models, particularly large architectures such as ResNet, Inception, or Transformers, demand substantial computational resources, including high-end GPUs and extended training times [20]. This poses challenges in resource-constrained environments such as rural or developing regions.

Moreover, most DL models function as "black boxes," offering limited interpretability. This lack of transparency hinders clinical trust and acceptance, as healthcare professionals often require explainable results to support decision-making [21]-[22].

D. Real-World Deployment and Clinical Validation

Despite high accuracy in controlled experimental settings, real-world deployment remains limited due to:

- The lack of clinical validation and peer-reviewed trials.
- Regulatory barriers and standardization issues in model evaluation.
- Integration challenges with existing healthcare information systems (HIS) and electronic medical records (EMR).

Models must undergo extensive validation across diverse demographics and conditions before being trusted for clinical use.

E. Ethical and Privacy Concerns

- The use of patient skin images raises ethical and privacy issues, including:
- Data privacy risks from storing and sharing sensitive medical images.
- Bias in datasets, which may lead to unfair outcomes for underrepresented populations (e.g., darker skin tones).

6. APPLICATIONS AND REAL-WORLD SYSTEMS

The integration of ML and DL in dermatological applications has led to the development of practical systems aimed at improving accessibility, affordability, and accuracy of skin disease diagnosis. These applications have become especially important in regions with limited access to dermatologists or advanced medical infrastructure.

A. Mobile-Based Skin Disease Diagnosis

`Smartphones equipped with high-resolution cameras and AI-based diagnostic apps have made it possible to screen and assess skin conditions on-the-go. These systems typically:

- Allow users to capture images of skin lesions using their smartphone.
- Use pre-trained ML/DL models to classify skin conditions in real time.
- Provide recommendations for further action (consult a specialist, over-the-counter treatment).

Examples include Skin Vision, Aysa, and Derma Check AI, which offer basic skin health assessments. Such tools empower users to conduct initial self-screening, particularly in areas where dermatological services are unavailable or expensive.

B. Integration with Telemedicine

The rise of telemedicine platforms has been accelerated by the COVID-19 pandemic, and AI-based skin disease diagnosis systems have become a natural extension of these platforms [23]. Key features include:

- Seamless integration of AI skin image analysis into virtual consultation workflows.
- Support for dermatologists by providing AI-driven second opinions or triage support.
- Streamlined documentation and faster diagnosis turnaround times.

This integration enhances remote consultations, reduces patient wait times, and helps prioritize serious cases for in-person visits.

C. Use in Remote and Rural Healthcare

In developing regions and rural communities where dermatologists are scarce, AI-powered diagnostic tools provide a cost-effective and scalable solution [24]. These systems can be deployed in:

- Community health centers, with support from local health workers.
- Portable devices or kiosks, requiring minimal infrastructure.
- Offline-capable apps, useful in areas with poor internet connectivity.

By enabling early detection and timely intervention, these systems can reduce the burden of skin diseases and improve public health outcomes in underserved areas.

CONCLUSION

The growing burden of skin diseases worldwide necessitates innovative, scalable, and accurate diagnostic solutions. Our review highlights the significant advancements made in the field of automated skin disease detection through ML and DL techniques. Traditional ML models offer simplicity and interpretability, while DL models—particularly CNNs and their variants—have demonstrated superior accuracy by learning complex features directly from images. Additionally, transfer learning, ensemble approaches, and attention mechanisms have further enhanced diagnostic performance.

Despite these advancements, several challenges persist, including limited availability of high-quality labeled datasets, risks of overfitting, high computational demands, and the need for clinical validation. Ethical and privacy issues also remain critical concerns in real-world deployment. However, the successful integration of AI into mobile platforms, telemedicine services, and rural healthcare systems signifies the growing maturity and accessibility of these technologies.

Looking forward, the continued success of AI in dermatological care will depend on sustained collaboration between dermatologists, data scientists, and engineers. Future research should prioritize data diversity, model interpretability, and patient-centered design to ensure these technologies are not only accurate but also trusted and usable in everyday clinical practice. By bridging the gap between computational innovation and clinical expertise, AI has the potential to revolutionize skin healthcare and improve outcomes for millions globally.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

FUNDING SUPPORT

The author declare that they have no funding support for this study.

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