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DEEP LEARNING-BASED SKIN DISEASE DETECTION AND PERSONALIZED SKINCARE: A COMPREHENSIVE REVIEW

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ABSTRACT

Skin diseases represent one of the most prevalent global health burdens, affecting over 900 million people worldwide. Traditional diagnostic methods relying on visual inspection by dermatologists face significant limitations, including subjectivity, limited accessibility in resource-constrained settings, and delayed treatment initiation. This paper presents a comprehensive review of deep learning-based approaches for automated skin disease detection and personalized skincare recommendation systems. We examine current methodologies encompassing convolutional neural networks (CNNs), transformer architectures, and hybrid models, analyzing their performance across multiple benchmark datasets including HAM10000 and ISIC. Our review synthesizes findings from recent studies demonstrating that hybrid approaches combining feature extraction from deep learning models with traditional machine learning classifiers achieve accuracy exceeding 98%. Furthermore, we investigate the integration of multimodal diagnostics combining image analysis with impedance sensing for comprehensive skin assessment. The paper addresses critical challenges including data imbalance, inter-class similarity, model interpretability, and generalization across diverse skin tones. Finally, we explore emerging directions in personalized skincare, including AI-driven formulation recommendation systems capable of generating millions of customized product combinations based on individual skin profiles.

KEYWORDS: Deep Learning, Skin Disease Detection, Convolutional Neural Networks, Transformers, Personalized Skincare, Multimodal Diagnostics, Computer-Aided Diagnosis

1. INTRODUCTION

1.1 Background and Motivation

Skin and subcutaneous diseases rank among the leading non-fatal health burdens worldwide, according to recent Global Burden of Disease analyses. Their high prevalence across diverse age groups and geographic regions underscores the widespread nature of dermatological conditions. According to the World Health Organization, more than 900 million people are affected by various skin conditions at any given time, with skin disorders representing the fourth leading cause of nonfatal disease burden globally.

The spectrum of skin diseases ranges from mild, self-limiting conditions to life-threatening malignancies. Skin cancer, particularly melanoma, remains one of the most prevalent and deadly forms of cancer worldwide, highlighting the critical importance of early detection and diagnosis in improving patient outcomes. Despite this burden, access to dermatological evaluation remains severely limited in many regions. The shortage of dermatology specialists, particularly in rural and low-resource settings, creates significant barriers to timely and accurate diagnosis.

Traditional diagnostic methods primarily rely on visual inspection by trained dermatologists, often supplemented by dermoscopy a non-invasive imaging technique that provides enhanced visualization of subsurface skin structures. While effective, these approaches face inherent limitations. Visual examination remains inherently subjective, with diagnostic accuracy varying significantly based on clinician experience. Furthermore, suspicious lesions often require biopsy and histopathological analysis for definitive diagnosis, procedures that are invasive, time-consuming, and expensive.

1.2 The Promise of Deep Learning in Dermatology

In recent years, deep learning (DL) has emerged as a transformative technology for medical image analysis, offering the potential to revolutionize skin disease diagnosis. Unlike traditional computer-aided diagnosis systems that rely on handcrafted features, deep learning models can automatically learn hierarchical representations of visual patterns directly from raw images. This capability enables the extraction of discriminative features such as color variations, irregular borders, and textural differences that are critical for distinguishing between various skin conditions.

Convolutional neural networks (CNNs) have been particularly successful in dermatological applications, demonstrating performance comparable to or exceeding that of board-certified dermatologists in controlled studies. The availability of large, well-annotated public datasets, including the International Skin Imaging Collaboration (ISIC) archive and the HAM10000 dataset, has been instrumental in advancing research in this domain.

1.3 The Personalization Paradigm

Beyond diagnosis, there is growing recognition that effective skincare requires personalization. Factors such as skin type, environmental exposure, lifestyle, and genetic predisposition significantly influence individual skin health and treatment responses. A recent Mintel report found that 62% of beauty and personal care consumers are interested in hyper-personalized products, with 28% willing to pay premium prices for such customization.

This has led to the emergence of AI-driven personalized skincare systems that integrate diagnostic capabilities with tailored product recommendations. These systems leverage multiple data modalities including facial imaging, user-provided information, and sometimes biophysical measurements to generate individualized skincare regimens.

1.4 Scope and Contribution of This Review

This paper provides a comprehensive review of deep learning-based approaches for skin disease detection and personalized skincare. Our contributions include:

1. A systematic analysis of deep learning architectures for skin lesion classification, including CNNs, transformers, and hybrid models
2. Quantitative comparison of model performance across benchmark datasets
3. Examination of multimodal approaches combining image analysis with complementary sensing modalities
4. Investigation of personalization frameworks for skincare recommendation
5. Critical discussion of challenges including data imbalance, interpretability, and generalization across skin tones
6. Identification of emerging research directions and future opportunities

2. Deep Learning Architectures for Skin Disease Detection

2.1 Convolutional Neural Networks

Convolutional neural networks form the foundation of most deep learning-based skin disease detection systems. These architectures are specifically designed to process grid-like data, making them particularly well-suited for image analysis tasks. The core building blocks of CNNs include convolutional layers that apply learnable filters to input images, pooling layers that reduce spatial dimensions, and fully connected layers that perform classification.

Res Net Architectures: Residual Networks (ResNet) introduced the concept of skip connections, allowing gradients to flow directly through the network and enabling the training of very deep architectures. In skin lesion classification, ResNet variants have demonstrated strong performance. A comprehensive evaluation by Dogan et al. found that ResNet18 achieved the highest accuracy of 98.06% among tested architectures for skin disease classification. ResNet34, ResNet50, and ResNet101 have all been extensively evaluated, with performance generally improving with increased depth, though with diminishing returns beyond certain thresholds.

Dense Net: DenseNet architectures take a different approach, connecting each layer to every other layer in a feed-forward fashion. This design promotes feature reuse and improves parameter efficiency. Studies have shown DenseNet121 achieving 96.27% accuracy on public dermatology datasets, with F1-scores of 96.20% . The dense connectivity pattern is particularly beneficial for medical imaging tasks where fine-grained features are critical for discrimination.

VGG Networks: The VGG family, characterized by its simple and uniform architecture of stacked convolutional layers, remains a strong baseline. VGG16 achieved an F1-score of 97.41% in comparative studies, while VGG19 demonstrated 96.80% accuracy on benchmark datasets.

MobileNet Architectures: For applications requiring deployment on mobile or resource-constrained devices, lightweight architectures such as MobileNetV2 offer efficient alternatives. When combined with support vector machines (SVM) for classification, MobileNetV2 achieved 98.08% accuracy, demonstrating that high performance need not require massive computational resources.

Table 1: Performance Comparison of CNN Architectories for Skin Disease Classification.

Architecture	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)
ResNet18	98.06	-	-	-	-
ResNet34	84.43	84.97	83.60	85.38	85.17
ResNet50	85.32	85.45	85.19	86.67	86.06
ResNet101	86.82	87.79	85.71	87.38	87.58
DenseNet121	96.27	96.20	96.10	96.70	96.20
VGG16	96.77	97.20	96.30	96.73	96.80
VGG19	95.27	95.10	95.60	96.19	95.80
MobileNetV2 + SVM	98.08	-	-	-	-

2.2 Transformer-Based Architectures

While CNNs have dominated medical image analysis, transformer architectures originally developed for natural language processing have recently emerged as powerful alternatives. Vision Transformers (ViT) and their variants leverage self-attention mechanisms to capture both local and global contextual relationships across image patches, addressing a key limitation of CNNs which primarily rely on local receptive fields.

Swin Transformer: The Shifted Window (Swin) Transformer introduces a hierarchical design with shifted window attention, enabling efficient computation while maintaining the ability to model long-range dependencies. In skin lesion classification, Swin Transformer architectures have demonstrated superior performance compared to CNN-based approaches. Swin Transformer Large achieved 92.78% accuracy, 92.96% sensitivity, 92.59% specificity, 93.40% precision, and 93.18% F1-score on public dermatology datasets. The Swin Transformer Base variant achieved 90.80% accuracy with corresponding metrics of 90.61% sensitivity, 91.01% specificity, 91.90% precision, and 91.25% F1-score.

The advantage of transformer architectures becomes particularly apparent when classifying conditions with subtle or diffuse visual patterns that span across different regions of the image, such as psoriasis or pox lesions. By capturing global contextual information, transformers can better distinguish between conditions that appear locally similar but differ in overall distribution patterns.

2.3 Hybrid Approaches

An emerging trend in skin disease detection involves hybrid approaches that combine the strengths of multiple architectures or integrate deep learning with traditional machine learning methods.

Deep Learning for Feature Extraction with Traditional Classifiers: Rather than using deep learning models for end-to-end classification, some approaches employ pre-trained CNNs as feature extractors, then use traditional machine learning classifiers such as Random Forest, Support Vector Machines, or Decision Trees for the final classification step. This approach leverages the powerful representation learning capabilities of deep networks while benefiting from the interpretability and efficiency of traditional classifiers.

Aquil et al. demonstrated this approach with remarkable results. Using DenseNet121 for feature extraction followed by Random Forest classification achieved 98.32% accuracy, representing one of the highest reported performance levels on this task. Similarly, MobileNetV2 feature extraction with SVM classification achieved 98.08% accuracy.

CNN-Transformer Hybrids: Recent research has explored integrating CNN and transformer components within unified architectures. These designs typically use CNN layers for local feature extraction in early stages, followed by transformer blocks for global context modeling. Such hybrid architectures aim to capture both fine-grained local patterns critical for identifying specific lesion characteristics and broader contextual relationships that aid in differential diagnosis.

3. Datasets and Evaluation Methodologies

3.1 Major Public Datasets

The progress in deep learning-based skin disease detection has been substantially enabled by the availability of large, well-annotated public datasets.

ISIC Archive: The International Skin Imaging Collaboration archive represents the most comprehensive resource for dermoscopic images. Through annual challenges, ISIC has provided thousands of expert-annotated dermoscopic images, driving competition and innovation in the field. The dataset includes images across multiple diagnostic categories with standardized annotations.

HAM10000: The Human Against Machine with 10000 training images dataset consists of 10,015 dermatoscopic images across seven diagnostic categories, making it one of the most diverse benchmarks for skin lesion classification. Categories include actinic keratoses, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, melanocytic nevi, and vascular lesions.

Mobile-Acquired Datasets: Recognizing that dermoscopic images do not reflect real-world clinical scenarios particularly in low-resource settings recent efforts have focused on curating datasets of mobile-captured skin images. One notable effort compiled over 27,000 images spanning more than 50 skin disease categories, representing one of the largest collections of non-dermoscopic skin images available for research.

3.2 Data Challenges

Class Imbalance: Medical datasets frequently exhibit significant class imbalance, with certain conditions substantially overrepresented compared to others. This poses challenges for model training, as networks may develop biases toward majority classes. Common mitigation strategies include oversampling minority classes, synthetic data generation using SMOTE (Synthetic Minority Over-sampling Technique), and weighted loss functions.

Domain Shift: When combining data from multiple sources, domain shift differences in image characteristics arising from different acquisition protocols, devices, or settings can substantially impact model generalization. Models trained on dermoscopic images often perform poorly on mobile-acquired images, and vice versa, highlighting the importance of matching training data to target deployment contexts.

Data Augmentation: To address limited dataset sizes and improve model robustness, data augmentation techniques are routinely employed. Common augmentations for skin images include random rotations, flips, zoom transformations, color jittering, and elastic deformations that simulate realistic variations in lesion appearance.

4. Multimodal Approaches to Skin Assessment

4.1 Combining Imaging with Impedance Sensing

While image-based analysis provides rich morphological information, it captures only surface characteristics. Electrical impedance sensing offers complementary information about

subsurface properties, particularly skin hydration and barrier function. Skin impedance is directly related to moisture content, making it a reliable indicator for hydration assessment .
A multimodal approach developed by researchers and published in Scientific Reports integrates both imaging and impedance sensing within a portable, low-cost device . This system captures both visual images and impedance measurements from the same skin location, enabling comprehensive assessment.

For moisture prediction tasks, the study found that Random Forest algorithms trained on impedance data outperformed both Linear Regression and Multilayer Perceptron (MLP) models. Notably, impedance-based data yielded better performance than image-based inputs for this specific task, highlighting the value of complementary sensing modalities.

Table 2: Performance Comparison for Skin Moisture Prediction.

Model	**Input Modality**	**MSE**	**R^2**
Linear Regression	Impedance	Baseline	Baseline
MLP	Impedance	Improved	Improved
Random Forest	Impedance	Best	Best
Random Forest	Image	Lower	Lower

For skin type classification, the study found that MLP models trained on handcrafted features from images outperformed CNN-based approaches applied to raw images. This finding highlights that for certain tasks, feature-engineered approaches may be more effective than end-to-end deep learning, particularly when training data is limited.

4.2 Integration of Biophysical and Environmental Data

Comprehensive skin assessment extends beyond imaging and impedance to incorporate additional factors influencing skin health. Modern personalized skincare systems integrate:

- **Skin type classification** (oily, dry, combination, normal, sensitive).
- **Acne severity assessment** (lesion counting and characterization).
- **Oiliness level quantification**
- **UV exposure history**
- **Environmental factors** (humidity, pollution, temperature).

This multidimensional data enables more accurate diagnosis and more effective personalization.

5. Personalized Skincare Recommendation Systems

5.1 From Diagnosis to Personalization

The ultimate goal of AI-driven dermatological systems extends beyond diagnosis to actionable recommendations tailored to individual patients. Personalized skincare represents a paradigm shift from one-size-fits-all approaches to customized interventions based on individual skin profiles.

The Universkin system, launched by Alma, exemplifies this approach. The system captures a facial image, analyzes skin characteristics, and generates personalized formulation recommendations selected from 487,678 possible combinations, yielding nearly 12 million potential outcomes . Within one minute of analysis, the AI recommends products tailored to the patient's specific skin profile and concerns.

5.2 AI-Driven Recommendation Frameworks

Sriram et al. proposed a comprehensive framework for AI-driven personalized skincare recommendations that integrates multiple data sources and analytical approaches:

K-Nearest Neighbors (KNN) for Product Recommendation: Using input features including skin type, acne count, oiliness level, and UV exposure, KNN algorithms identify similar user profiles and recommend products that have been effective for those with comparable characteristics.

Natural Language Processing for Regimen Generation: NLP techniques analyze unstructured data from product reviews and user problem descriptions to develop tailored 7-day skincare regimen recommendations. This approach transforms qualitative user feedback into quantitative, actionable insights.

Deep Learning for Real-Time Assessment: CNN-based models enable real-time image-based assessment of skin conditions, facilitating precise acne diagnosis and oiliness evaluation without requiring specialized equipment.

5.3 Feedback Integration and Continuous Improvement

A key feature of effective personalization systems is their ability to learn from user feedback. By incorporating outcomes data whether users experienced improvement, no change, or adverse reactions systems can continuously refine their recommendations. This feedback loop enables adaptive personalization that improves over time.

6. Challenges and Limitations

6.1 Model Interpretability

A critical requirement for clinical adoption of deep learning systems is interpretability the ability to understand why a model made a particular prediction. In medical applications, "black box" predictions are insufficient; clinicians and patients need to trust and validate diagnostic outputs.

Grad-CAM for Visualization: Gradient-weighted Class Activation Mapping (Grad-CAM) has emerged as a popular technique for visualizing model attention. By generating heatmaps overlaid on original images, Grad-CAM shows which regions most strongly influenced model predictions. This enables verification that models are focusing on clinically relevant lesion areas rather than background artifacts or spurious correlations.

Studies applying Grad-CAM to skin lesion classification have demonstrated that well-trained models do indeed focus on diagnostically relevant features, including lesion borders, color variation, and textural abnormalities. This visualization capability enhances both clinician confidence and model trustworthiness.

6.2 Generalization Across Skin Tones

A significant limitation of many existing skin disease detection systems is their poor generalization across diverse skin tones. Most training datasets are heavily biased toward lighter skin tones, potentially leading to reduced accuracy for individuals with melanin-rich skin.

This disparity is particularly concerning given that certain skin conditions present differently across skin tones. For example, erythema (redness) may be clearly visible on light skin but substantially more difficult to detect on darker skin. Similarly, conditions like psoriasis may exhibit different coloration patterns depending on skin pigmentation.

Aquil et al. specifically addressed this challenge, noting that skin diseases in melanin-rich skin present unique diagnostic challenges due to the distinct characteristics of darker skin tones. Their hybrid approach using DenseNet121 with Random Forest classification demonstrated robust performance across diverse populations, though they acknowledge that further work is needed to ensure equitable performance.

6.3 Data Imbalance and Rare Conditions

While major datasets cover common conditions adequately, rare skin diseases remain substantially underrepresented. This limits the ability to develop models capable of detecting unusual or uncommon conditions precisely the scenarios where diagnostic assistance might be most valuable.

Mitigation strategies include transfer learning from related tasks, few-shot learning approaches, and synthetic data generation. However, these remain active research areas without definitive solutions.

6.4 Clinical Integration

Despite promising research results, integration of deep learning systems into clinical workflows remains limited. Barriers include:

- **Regulatory approval requirements** for medical devices and software.
- **Liability concerns** regarding AI-assisted diagnosis.
- **Workflow integration challenges** with existing electronic health records.
- **Clinician acceptance** and trust in automated systems.
- **Reimbursement uncertainty** for AI-facilitated consultations.

Addressing these implementation barriers is essential for translating research advances into clinical practice.

7. Emerging Directions and Future Opportunities

7.1 Hybrid CNN-Transformer Architectures

Recent research suggests that hybrid architectures combining CNN and transformer components may offer the optimal balance of local feature extraction and global context modeling. These designs typically employ CNN layers for early-stage feature extraction, capitalizing on their efficiency for local pattern recognition, followed by transformer blocks for higher-level contextual integration.

7.2 Uncertainty-Aware Models

Standard deep learning models produce point predictions without conveying confidence information. In medical applications, however, understanding when a model is uncertain is nearly as important as the prediction itself. Uncertainty-aware models that provide confidence estimates enable appropriate human oversight high-confidence predictions might be accepted automatically, while low-confidence cases would trigger expert review.

Techniques for uncertainty quantification include Bayesian neural networks, Monte Carlo dropout, and ensemble methods. These approaches are particularly valuable for rare conditions where training data is limited.

7.3 Foundation Models for Dermatology

The emergence of large foundation models models pre-trained on massive, diverse datasets and fine-tuned for specific tasks represents a promising direction. A dermatological foundation model trained on millions of skin images across diverse conditions, skin tones, and imaging modalities could provide a powerful starting point for numerous downstream tasks, including disease classification, severity assessment, and treatment monitoring.

7.4 Integration with Wearable Devices

The proliferation of wearable devices capable of monitoring environmental exposures, stress levels, sleep patterns, and other factors relevant to skin health opens new possibilities for continuous, personalized skincare. Integration of image-based assessment with longitudinal wearable data could enable dynamic personalization that adapts to changing conditions and contexts.

7.5 Teledermatology and Global Health

Perhaps the most significant potential impact of deep learning-based skin disease detection is in expanding access to dermatological care in underserved regions. Mobile-based systems requiring only a smartphone camera could enable screening and triage in areas without dermatology specialists. Combined with telemedicine platforms for expert consultation when needed, such systems could substantially reduce disparities in dermatological care access .

8. CONCLUSION

Deep learning-based approaches for skin disease detection and personalized skincare have advanced substantially in recent years, demonstrating performance that often matches or exceeds human expert levels on specific tasks. Convolutional neural networks remain the workhorse of most systems, though transformer architectures and hybrid approaches are showing promising results, particularly for complex cases requiring global contextual understanding.

The integration of multiple data modalities combining image analysis with impedance sensing, biophysical measurements, and environmental data enables more comprehensive assessment than any single modality alone. Similarly, the evolution from pure diagnosis to personalized recommendation represents a significant advance, moving from identifying conditions to suggesting individualized interventions.

Substantial challenges remain, including ensuring equitable performance across diverse skin tones, developing interpretable models that clinicians can trust, and navigating the regulatory and implementation barriers to clinical deployment. Addressing these challenges will require continued collaboration between computer scientists, dermatologists, regulatory bodies, and industry partners.

The potential impact of successful deployment is substantial: improved diagnostic accuracy, reduced healthcare costs, expanded access to dermatological care, and more effective, personalized treatments for the millions worldwide affected by skin diseases.

REFERENCES

1. "Multimodal skin care system using combined image and impedance-based diagnostics," *Scientific Reports*, vol. 16, Article 4168, 2026.
2. "Performance of proposed models and other SOTA methods on different dataset," *Nature Scientific Reports*, Table 2, 2024.
3. K. Sriram et al., "AI-Driven Personalized Skincare Recommendations," *2025 International Conference on Electronics and Renewable Systems (ICEARS)*, pp. 1086-1091, 2025.
4. R. Liu et al., "Exploring the Challenge and Value of Deep Learning in Automated Skin Disease Diagnosis," *arXiv preprint arXiv:2510.03869*, 2025.
5. A. Aquil, F. Saeed, S. Baowidan, A. M. Ali, N. S. Elmitwally, "Early Detection of Skin Diseases Across Diverse Skin Tones Using Hybrid Machine Learning and Deep Learning Models," *Information*, vol. 16, no. 2, p. 152, 2025.
6. "A Machine Learning Framework for Accurate Skin Tone, Type, and Disease Detection with Web Scraping and NLP for Dermatological Insights," *IEEE Xplore*, 2025.
7. F. Doğan, M. Aktaş, M.İ. Gürsoy, "Classification of Skin Diseases with Different Deep Learning Models and Comparison of the Performances of the Models," *TDFD*, vol. 13, no. 3, pp. 117-123, 2024.

8. "Alma Unveils AI-Driven Universkin Skincare System," *Global Cosmetic Industry*, July 2025.
9. J. Liu, L. Liu, X. An, "Deep Learning for Classification and Prognosis of Melanoma in Whole-Slide Images: A Review," *The American Journal of Dermatopathology*, February 2026.
10. A. N. Masum et al., "Toward Accessible Dermatology: Skin Lesion Classification Using Deep Learning Models on Mobile-Acquired Images," *arXiv preprint arXiv:2509.04800*, 2025.