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Eczema Detection in Dermatological Imaging: From Traditional Methods to Deep Learning and Mobile Deployment

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Abstract

Atopic dermatitis or eczema is a chronic inflammatory skin condition. This disease is characterized by recurrent redness, itching, and irritation. Its clinical significance lies in its long-term discomfort and significant impact on an individual's quality of life. Traditionally, the diagnosis of eczema has relied on visual examination by a dermatologist, patient interviews, and manual assessment using a clinical scoring system. Although effective, these methods are limited by interobserver variability, inconsistencies in clinical expertise, and scalability challenges. This is particularly true in settings with limited dermatology resources. These limitations underscore the need for more objective, accessible, and technology-driven diagnostic approaches. This paper reviews the evolution of eczema detection, tracing the transition from conventional clinical assessment to modern algorithm-assisted methods. It highlights advances in medical imaging, feature extraction techniques, and sophisticated deep learning models, with particular emphasis on their suitability for mobile and real-time use. Treatment strategies and non-dermatological conditions are intentionally excluded to maintain the focus on diagnostic innovation. Overall, this review provides a comprehensive analysis of historical practices, recent technological advances, existing challenges, and emerging opportunities in automated eczema detection.

1. Introduction

Atopic dermatitis, or eczema, is a chronic inflammatory skin disease that affects millions of people worldwide. It is commonly marked by dry skin, itching, and red or irritated patches. Symptoms often begin in childhood and can persist or recur throughout life [1]. The condition not only causes physical discomfort but also affects mental well-being, sleep, and daily productivity. Eczema presents in many different forms. Its variations are influenced by genetics, environmental factors, and skin barrier disfunction [2]. Patients may experience intense itching, inflammation, flaking skin, or thickened patches. These diverse symptoms make eczema difficult to identify consistently, even for experienced clinicians.

The number of eczema cases continues to rise globally, especially in urban areas. Early and accurate diagnosis is therefore increasingly important. Traditionally, diagnosis is based on visual examination and patient history. Clinicians also use scoring systems such as Scoring Atopic Dermatitis (SCORAD) and Eczema Area and Severity Index (EASI). SCORAD evaluates the extent, intensity, and symptoms of eczema, while EASI measures the severity and affected body areas. Although useful, these tools depend heavily on human judgment. As a result, they often yield inconsistent results across clinicians, leading to inconsistent assessments.

Traditional methods also require trained dermatologists and access to clinical facilities. This creates challenges in areas with limited medical resources [4]. Because of these limitations, there is a growing need for new detection methods that are more objective, scalable, and accessible. Recent advances in imaging, machine learning, and mobile technology offer promising solutions. Deep learning models can analyze skin images and improve detection consistency. Mobile deployment can also bring these tools to underserved regions, making early diagnosis more accessible. Unlike existing review papers, this article shares the full range of eczema detection methods. It covers traditional clinical practices to modern deep learning and mobile-based approaches. It highlights current progress, remaining challenges, and future directions for improving eczema diagnosis through technology.

This paper contains several sections. It begins with an introduction and is followed by traditional methods for detecting eczema. Section 3 discusses the computerized Image-Based and Machine Learning Methods. While Section 4 discusses Deep Learning and Convolutional Neural Networks in Eczema Detection. Section 5 presents Deployment Considerations, Challenges, and Future Directions. The last section gives a conclusion.

2. Traditional Methods for Eczema Detection

The diagnosis of eczema has historically relied on a combination of clinical observation and patient history obtained by dermatologists. Clinicians examine the patient's skin for key indicators such as erythema, inflammation, crusting, oozing, and lichenification (thickened skin) [5]. The distribution of lesions and the pattern of symptoms provide additional context that supports diagnostic decisions. In parallel, a detailed symptom and lifestyle history is collected to help identify potential triggers and contributing factors. Table 1 outlines four essential components of patient history that commonly guide diagnosis and treatment planning.

Table 1 *Key Components of patient history in traditional eczema diagnosis*

Component	Description	Clinical Relevance
Onset and Duration	Determines when the symptoms first appear and how long they persist in a flare-up.	Help differentiate eczema from other dermatological conditions with similar presentations.
Trigger Identification	Identifies environmental, dietary, or lifestyle factors that worsen symptoms.	Supports personalized treatment and avoidance strategies.
Family and Medical History	Assesses history of atopic diseases (e.g., asthma, allergic rhinitis) within the family.	Provides insight into genetic predisposition.
Symptom Pattern and Severity	Evaluates itch intensity, sleep disturbance, and frequency of flare-ups.	Guides severity classification and treatment planning.

Table 2 *Scoring systems*

Scoring System	Key Components	Purpose	Strengths	Limitations
Scoring Atopic Dermatitis (SCORAD)	Assessing the extent of affected areas, intensity of symptoms (erythema, edema, excoriation, etc.), and subjective symptoms such as itching and sleep loss.	Provides a combined clinical and symptomatic evaluation of eczema severity.	Combines both objective and subjective measures; widely used in clinical research.	Subjective elements (e.g., itch severity) may reduce scoring consistency.
Eczema Area and Severity Index (EASI)	Measures the severity of four signs which are erythema, edema/papulation, excoriation, and lichenification.	Offers a structured, fully objective method for assessing eczema severity.	Eliminates subjective reporting; improves inter-clinician consistency.	Does not consider symptoms such as itching or sleep disturbance.

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To complement visual assessment and history-taking, standardized scoring systems are used to quantify disease severity. These tools promote consistent evaluation and facilitate communication across healthcare providers. Table 2 summarizes the two most widely used scoring systems which are SCORAD and EASI. It highlights their components and clinical utility. Both scoring mechanisms provide structured, qualitative, and quantitative measures of eczema severity. It assists clinicians in treatment planning and monitoring disease progression over time [6]. They allow dermatologists to systematically assess changes, improving the reliability of follow-up evaluations.

Traditional diagnostic techniques offer several strengths. The most important is the clinical expertise of dermatologists, who draw on years of experience to make accurate and often precise assessments. Clinical examinations also provide immediate feedback, allowing for real-time discussions with patients about their condition. Standardized scoring systems, such as SCORAD and EASI, further enhance consistency and allow for comparisons across different clinical settings [7].

Despite these advantages, traditional approaches also present significant limitations. A primary challenge is inter-observer variability, where clinicians may interpret signs differently, leading to inconsistent diagnoses [8]. These methods are also time-consuming and require specialized expertise, which may not be available in rural or resource-limited regions [9]. As a result, access to accurate diagnosis remains uneven. Additionally, traditional assessments are labor-intensive, making large-scale screening impractical and restricting early detection in broader populations.

Even with standardized scoring systems, subjectivity cannot be fully removed. Differences in scoring or interpretation may affect the reliability and reproducibility of results. Furthermore, traditional diagnostic methods generally lack integration with modern technologies and data analytics, limiting opportunities to enhance diagnostic precision, automate assessments, and scale services efficiently.

3. Computerized Image-Based and Machine Learning Methods

Early efforts to integrate technology into eczema detection centered on traditional image processing techniques and machine learning models that relied heavily on handcrafted features. These features were manually designed descriptors extracted from skin lesion images such as color patterns, texture variations, and lesion shapes. Researchers use the features to distinguish eczema from other skin conditions [10]. Table 3 provides an overview of commonly used handcrafted features and their clinical relevance.

Table 3 *Common handcrafted features used in early eczema detection*

Feature	Description
Color Histogram	Examines the distribution of color intensities within a lesion to identify redness or discoloration associated with eczema.
Texture Analysis	Uses methods such as Local Binary Patterns (LBP) or the Gray-Level Co-occurrence Matrix (GLCM) to quantify surface roughness, scaling, or dryness.
Shape Features	Measures contour irregularities, size, and geometry of lesions to support early classification distinctions.

Once extracted, these features were typically fed into classical machine learning algorithms such as Support Vector Machines (SVMs) and Random Forests. SVMs aimed to identify the optimal hyperplane that separates lesion categories. Random Forest models utilize multiple decision trees to improve classification accuracy and reduce overfitting. These early computational approaches represented a significant advance over purely subjective clinical assessments. They introduced measurable structure and repeatability into the diagnostic process.

Despite these improvements, handcrafted feature-based techniques suffered from several notable limitations. A key challenge was the wide variation in skin tones among patients, which led to inconsistent interpretation of color-based features and often introduced diagnostic bias [11]. Additionally, variations in image acquisition, such as poor lighting, shadows, or low-quality camera sensors, can distort color and texture information. It then further reduces feature reliability.

Another major limitation relates to the morphological diversity of eczema. lesions vary greatly in size, shape, severity, and appearance across individuals and body locations [12]. This variability reduced the ability of handcrafted features to capture the full spectrum of eczema presentations. It leads to weaker generalization during classification.

Consequently, models trained on specific datasets often performed poorly on new, unseen cases, leading to misclassification and reduced clinical usefulness. The reliance on expert-defined features also introduced human bias and limited adaptability, particularly when confronted with atypical manifestations of disease. These

limitations highlighted the need for more robust, automated, and data-driven approaches. It motivates the shift toward deep learning and end-to-end feature learning in modern eczema detection systems.

4. Deep Learning and Convolutional Neural Networks in Eczema Detection

Deep learning has greatly enhanced automated eczema detection by providing superior accuracy, greater reliability, and greater scalability compared to conventional machine learning methods reliant on manually designed features. Previous research relied on color, texture, and edge-based features, along with classifiers such as support vector machines. This showed limited generalization due to their susceptibility to lighting changes and variability in lesion appearance. Conversely, convolutional neural networks (CNNs) autonomously acquire hierarchical feature representations straight from images. It leads to significantly enhanced classification accuracy for various eczema manifestations.

Recent research using pretrained CNN models such as VGG16, MobileNet, and EfficientNet consistently outperforms previous shallow CNNs and traditional techniques by leveraging transfer learning from large-scale image datasets. For instance, models based on EfficientNet achieve higher accuracy and lower parameter count than VGG-based architectures, making them more appropriate for mobile and resource-limited clinical use. Nevertheless, deeper models may overfit when trained on limited dermatological datasets, underscoring the importance of using data augmentation and regularization techniques.

Lightweight CNNs and MobileNet variants excel in mobile applications due to their lower computational requirements and faster inference speeds. although they might show marginally reduced accuracy relative to deeper networks when trained on smaller datasets. To address this trade-off, various studies use ensemble learning and attention mechanisms, thereby enhancing robustness by focusing on clinically significant lesion areas and minimizing background noise. These techniques are especially effective at managing differences in skin color, lighting, and image quality.

Challenges remain despite these advances. Deep learning models often fail when exposed to unseen eczema subtypes or images captured under non-standard conditions. This is largely due to data set bias and limited clinical annotation. This underscores the need for larger, more diverse datasets and explainable AI techniques to improve clinical confidence and generalizability. Overall, the reviewed studies show a clear development from hand-crafted feature methods to sophisticated CNN-based frameworks. It is driven by performance improvements enabled by feature learning, architectural efficiency, and data-centric optimization.

4.1 Pretrained Architectures and Transfer Learning

Recent eczema detection studies rely heavily on deep learning, especially Convolutional Neural Networks (CNNs). Pretrained models such as VGG16, MobileNet, and EfficientNet are now widely used for skin-lesion classification tasks [13]. These models were trained on large and diverse datasets, enabling them to learn general visual features that transfer well to medical images.

Transfer learning plays a central role in this process. It allows researchers to fine-tune existing pretrained models instead of training from scratch. This reduces training time and computational cost while improving performance with limited dermatology datasets [14]. Fine-tuned CNNs commonly use categorical cross-entropy loss to optimize predictions in multiclass eczema classification tasks.

EfficientNet-B4 is frequently highlighted for its compound scaling strategy. Here, the depth, width, and input resolution expand uniformly. This architecture improves accuracy while maintaining relatively low parameter counts [15], [16]. EfficientNet-B4 uses an input size of 380×380 pixels and about 19 million parameters. making it suitable for both mobile and clinical use. As noted in [17], this model has achieved accuracy rates up to 95.8% in eczema detection tasks.

4.2 Custom CNN for Mobile Deployment

Lightweight custom CNNs have garnered attention for mobile and edge computing deployments. These models aim to provide fast inference with a minimal memory footprint. Quantization is a common optimization technique. It reduces the numerical precision of model weights, decreasing storage size and speeding up computation with minimal accuracy loss [18]. Other parameter-reduction strategies include pruning, which is removing less important neurons. It then uses depthwise separable convolutions. These techniques reduce model complexity and enhance mobile execution efficiency.

A mobile-focused custom CNN offers full control over design choices, including layer depth, kernel sizes, and activation functions. This allows developers to tailor the architecture specifically for eczema classification. Studies show that combining parameter reduction with quantization enables smooth on-device execution while maintaining high diagnostic accuracy [16], [17], [19], [20]. These developments make mobile CNNs practical for real-time eczema detection, particularly in teledermatology settings or those with limited access to specialists.

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4.3 Ensemble Models and Augmentation

Ensemble models have gained attention in recent years. They combine predictions from multiple CNNs to improve diagnostic accuracy in eczema detection. These models benefit from diverse architectures, which enable them to better handle variations in eczema lesions including differences in size, shape, and overall appearance. Attention mechanisms are often integrated into ensemble designs. These mechanisms enable the model to focus on important regions in the image, particularly active lesions. By focusing on clinically relevant areas, the model can classify eczema more accurately.

Data augmentation also plays an essential role. Techniques such as rotation, scaling, flipping, and color adjustments increase the variety of training images. This improves model robustness and helps prevent overfitting. As a result, the models generalize better to new and unseen eczema cases. Hybrid 6 Networks offer another advanced approach. They combine several CNNs through ensemble averaging and incorporate attention modules to highlight key lesion regions. These networks also rely heavily on augmentation techniques, including rotation and scaling, to expand dataset diversity and reduce overfitting [16, 17, 19, 20].

Ensemble and hybrid networks outperform single CNN architectures in eczema detection by combining predictions from multiple models. These models also integrate attention mechanisms and use extensive data augmentation. While single CNNs may be simpler and faster, they are less robust to variations in lesion appearance, size, and shape. This results in single CNNs producing lower overall accuracy. In contrast, ensemble models achieve higher diagnostic accuracy. However, ensemble models are more complex, less interpretable, and more computationally intensive. These characteristics limit real-time use on mobile or resource-constrained devices. In contrast, single or lightweight CNNs offer greater usability and faster inference. However, at the expense of slightly reduced accuracy and sensitivity to lesion variability.

Table 4 *Deep learning approaches for eczema detection*

Category	Description / Key Points	Examples / Notes
Pretrained CNN Architectures	Widely used for eczema and skin-lesion classification; trained on large datasets and transferable to medical imaging tasks.	VGG16, MobileNet, EfficientNet [13]
Transfer Learning	Fine-tuning pretrained models reduces training time and computational cost; effective for small dermatology datasets.	Uses categorical cross-entropy loss for multiclass classification [14]
EfficientNet-B4	Compound scaling improves accuracy while maintaining low parameter count; suitable for clinical and mobile applications.	Input 380×380 pixels; ~19M parameters; accuracy up to 95.8% [15–17]
Custom Lightweight CNNs	Designed for mobile and edge deployment; small models with fast inference and reduced memory footprint.	Tailored control of layers, kernels, activation functions
Quantization	Reduces the precision of weights to shrink model size and increase speed, with minimal loss of accuracy.	Important for mobile execution [18]
Parameter Reduction	Techniques to simplify model architecture while maintaining accuracy.	Pruning, depthwise separable convolutions
Mobile Deployments (Studies)	Research shows high diagnostic accuracy with optimized lightweight CNNs for on-device use.	[16], [17], [19], [20]
Ensemble Models	Combine predictions from multiple CNNs to improve diagnostic accuracy and handle diverse lesion appearances.	Ensemble averaging of CNN outputs
Attention Mechanisms	Allow models to focus on clinically relevant lesion regions to enhance classification accuracy.	Often integrated in ensemble and hybrid models
Data Augmentation	Expands dataset variety; improves generalization and reduces overfitting.	Rotation, scaling, flipping, color adjustments
Hybrid 6 Networks	Combine multiple CNNs, incorporate attention modules, and utilize extensive data augmentation to enhance accuracy.	Uses rotation and scaling; improves robustness [16, 17, 19, 20]

Table 4 provides a structured overview of the main deep learning approaches for eczema detection. The methods are categorized into pre-trained CNN architectures, transfer learning strategies, custom lightweight models, and ensemble or hybrid networks that combine attention and data augmentation. For each category, the table lists the purpose, key features, and representative studies or implementations. For example, EfficientNet-B4 demonstrates compound scaling to balance model accuracy and size, while custom CNNs use techniques such as quantization, pruning, and deep separable convolution to support mobile inference. Ensemble and hybrid models combine multiple CNNs with attention and augmentation strategies. Overall, the table reviews the technical strategies and practical considerations for deep learning-based eczema detection but does not offer evaluative or interpretive commentary.

In summary, deep learning approaches offer substantial improvements in eczema detection compared to traditional methods. Pretrained architectures and transfer learning reduce training time and improve performance on limited datasets. Custom lightweight CNNs allow efficient deployment on mobile and edge devices. Ensemble models, attention mechanisms, and data augmentation further increase accuracy and robustness across diverse lesion presentations. Overall, these techniques demonstrate the potential for automated, scalable, and real-time eczema detection systems, providing reliable diagnostic support in both clinical and remote healthcare settings.

Ensemble and hybrid deep learning models have demonstrated superior accuracy and robustness in eczema detection. Translating these approaches into real-world clinical and mobile settings requires careful consideration of implementation challenges. These include computational requirements, interpretability, data privacy, and scalability. Therefore, this translation process needs to be carried out properly to produce accurate results.

5. Deployment Considerations, Challenges and Future Directions

Mobile and teledermatology applications have become essential for improving access to dermatological care, particularly in rural and underserved regions [21]. These applications enable remote monitoring and diagnosis of skin diseases, including eczema, thereby enabling timely interventions and follow-ups. However, deploying on mobile or edge devices introduces unique constraints, such as limited memory and processing power, as well as device variability. Lightweight, optimized models are crucial for ensuring fast processing and real-time feedback, thereby enhancing patient outcomes in areas with scarce healthcare services.

Despite the potential benefits, several challenges remain. Image quality may vary due to differences in lighting conditions or camera capabilities [22]. It can reduce diagnostic accuracy. Effective user training is essential to prevent errors in image capture or data entry. Regulatory compliance also poses a challenge, as patient data must be protected in accordance with local healthcare laws. Addressing these challenges is essential to ensure that mobile and teledermatology solutions are safe, reliable, and widely adoptable.

Current limitations in eczema detection further extend to algorithmic and dataset constraints. Many datasets lack diversity in skin tones, lesion types, and severity levels, contributing to biases in model performance. Standardizing severity scoring systems, expanding datasets to include broader populations, and aligning algorithmic outputs with clinical standards are crucial for enhancing model interpretability and fairness. Additionally, the “black box” nature of deep learning algorithms reduces clinicians' trust. This reveals the need for explainable AI techniques that clarify decision-making processes.

Future directions in eczema detection should focus on longitudinal monitoring to track disease progression. It enables early detection of flare-ups and personalized management. Optimizing mobile and edge devices, refining user interfaces, and ensuring robust performance will support wider adoption. Advanced frameworks, such as federated learning, can enhance model performance while preserving patient privacy. Clinical validation through controlled trials remains essential to confirm the safety, reliability, and integration of these treatments into real-world dermatology practice. Collectively, addressing deployment, data, and algorithmic challenges will facilitate the development of more accurate, accessible, and patient-centered eczema detection systems.

Table 5 summarizes the key considerations, challenges, and future directions for deploying mobile and edge-based eczema detection systems. It categorizes the factors that influence successful implementation, ranging from technical constraints, such as device memory and processing limitations, to clinical and regulatory aspects, including data privacy, explainability, and validation. The table also highlights issues related to image quality, user training, and dataset diversity, which are critical to ensuring reliable and unbiased diagnostic outcomes. Future directions focus on strategies to improve model performance, accessibility, and patient-centered care. such as longitudinal monitoring, federated learning, and optimized user interfaces. Overall, the table provides a concise overview of the practical, technical, and ethical considerations required for the real-world adoption of mobile eczema-detection applications.

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Table 5 *Deployment considerations, challenges, and future directions in mobile eczema detection*

Category	Key Points / Considerations	Examples / Notes
Mobile Deployment	Enables remote monitoring and diagnosis, improves access in underserved areas	Teledermatology applications [21]
Resource Constraints	Mobile/edge devices have limited memory and processing power; lightweight, optimized models are required	Fast inference, real-time feedback
Image Quality	Lighting conditions and camera differences affect diagnostic accuracy	Requires standardization and user guidance [22]
User Training	Proper training reduces errors in image capture and data entry	Critical for reliable remote diagnosis
Regulatory Compliance	Patient privacy and data security must comply with local laws	HIPAA-like standards; secure cloud storage
Dataset Limitations	Lack of diversity in skin tones and lesion types leads to bias	Need for standardized and inclusive datasets
Algorithm Transparency	"Black box" models reduce clinician trust	Explainable AI for model interpretability
Clinical Validation	Controlled trials and prospective studies ensure efficacy and safety	Integration into standard practice
Future Directions	Longitudinal monitoring, mobile/edge optimization, federated learning, improved UI	Supports continuous patient management and privacy preservation

Advances in deep learning, including pretrained CNNs, lightweight custom models, and ensemble networks, have significantly improved the accuracy and efficiency of automated eczema detection. These models, as summarized in Table 4, provide scalable solutions that can operate in clinical and mobile contexts, leveraging transfer learning, quantization, attention mechanisms, and data augmentation to enhance robustness and generalization. However, the practical deployment of these systems, particularly on mobile and edge devices, introduces additional considerations as highlighted in Table 5. Resource constraints, image variability, user training, regulatory compliance, and dataset diversity all influence the reliability and accessibility of mobile eczema detection applications. Future directions emphasize longitudinal monitoring, explainable AI, federated learning, and optimized interfaces to ensure that these technologies are not only accurate but also clinically interpretable, secure, and widely adoptable. Together, these developments demonstrate a comprehensive pathway from advanced algorithmic design to real-world implementation, bridging technical innovation with practical healthcare delivery.

6. Conclusions

In summary, the detection of eczema has undergone considerable evolution. The transition from traditional clinical assessments to advanced deep learning-based approaches has offered improved accuracy, early detection, and the potential for mobile deployment. Thereby, the new technology can expand access to dermatological care in rural and underserved areas. Deep learning models, particularly those optimized for mobile and edge devices, demonstrate substantial promise for real-time, scalable, and patient-centered eczema monitoring. The challenges remain despite these advancements, which enable improvements suited to current needs. Algorithmic bias resulting from limited dataset diversity can impact diagnostic performance across diverse populations. Validation in real clinical settings is essential to ensure reliability, gain clinician trust, and integrate automated systems as complementary tools rather than replacements for professional judgment. Future directions should focus on addressing the limitations of mobile and edge devices. It safeguards patient data, expands dataset diversity, and aligns algorithm outputs with clinical standards. By overcoming these challenges, these innovative approaches can significantly enhance eczema detection and management, ultimately improving patient outcomes and quality of life.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors are responsible for the study conception, research design, data collection, data analysis, result interpretation and manuscript drafting.

References

[1] Tokura, Y., Yunoki, M., Kondo, S., & Otsuka, M. (2025). What is “eczema”?. The Journal of Dermatology, 52(2), 192-203.

[2] Spiewak, R. (2023). Diseases from the spectrum of dermatitis and eczema: Can “omics” sciences help with better systematics and more accurate differential diagnosis?. International Journal of Molecular Sciences, 24(13), 10468.

[3] Panahi, O. (2025). Deep Learning in Diagnostics. Journal of Medical Discoveries, 2(1), 1-6.

[4] Kumar, S., Saeed, A. G. F., & Bangash, S. A. (2024). ARTIFICIAL INTELLIGENCE IN DERMATOLOGY. Rheumatology, 41(8), 2345-2352.

[5] Peate, I. (2025). The skin. John Wiley & Sons.

[6] Stidham, R. W., & Takenaka, K. (2022). Artificial intelligence for disease assessment in inflammatory bowel disease: how will it change our practice?. Gastroenterology, 162(5), 1493-1506.

[7] Suresh, S., & Kaliyadan, F. (2025). Assessing eczema severity: a comprehensive review of scoring systems. Indian J Skin Allergy, 4, 19-24.

[8] Quinn, L., Tryposkiadis, K., Deeks, J., De Vet, H. C., Mallett, S., Mokkink, L. B., ... & Sitch, A. (2023). Interobserver variability studies in diagnostic imaging: a methodological systematic review. The British Journal of Radiology, 96(1148), 20220972.

[9] Muller, I., Stuart, B., Sach, T., Yardley, L., Greenwell, K., Becque, T., ... & Santer, M. (2025). Supporting self-care for eczema in the community: the Eczema Care Online research programme including two RCTs. Programme Grants for Applied Research, 13(3), 1-92.

[10] Gupta, P., Nirmal, J., & Mehendale, N. (2025). A survey on computer vision approaches for automated classification of skin diseases. Multimedia Tools and Applications, 84(11), 8673-8705.

[11] Kamp, E., Ascott, A., & George, S. M. (2025). Eczema Severity Scoring in Skin of Color: A Review of Current Best Practice and Need for Future Improvement. Journal of Investigative Dermatology.

[12] Bosma, A. L., Ascott, A., Iskandar, R., Farquhar, K., Matthewman, J., Langendam, M. W., ... & Middelkamp‐Hup, M. A. (2022). Classifying atopic dermatitis: a systematic review of phenotypes and associated characteristics. Journal of the European Academy of Dermatology and Venereology, 36(6), 807-819.

[13] Shams, M. Y., Hassan, E., Gamil, S., Ibrahim, A., Gabr, E., Gamal, S., ... & Bhatnagar, R. (2025). Skin Disease Classification: A Comparison of ResNet50, MobileNet, and Efficient-B0. Journal of Current Multidisciplinary research, 1(1), 1-7.

[14] Alnuaimi, M. N., Alqahtani, N. S., Gollapalli, M., Rahman, A., Alahmadi, A., Bakry, A., ... & Al-Musallam, H. (2024). Transfer Learning Empowered Skin Diseases Detection in Children. CMES-Computer Modeling in Engineering & Sciences, 141(3).

[15] Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. In Proceedings of the 36th International Conference on Machine Learning (ICML 2019) (Vol. 97, pp. 6105–6114).

[16] Ahmad, G., Saleem, M., Malik, J. A., Bukhari, W. A., Kashif, M. I., Salahuddin, H., & Ur Rehman, A. (2024). Mobile application for skin disease classification using CNN with user privacy. Journal of Computing & Biomedical Informatics.

[17] Yi, Z., Zhang, Y., Wang, S., & Chen, X. (2023). HI MViT: A lightweight model for explainable skin disease classification based on modified MobileViT. PMC.

[18] Goswami, M., Mohanty, S., & Pattnaik, P. K. (2024). Optimization of machine learning models through quantization and data bit reduction in healthcare datasets. Franklin Open, 8, 100136.

[19] Ahmed, S., Khan, S., & Ullah, I. (2023). Multi-class skin lesion classification using a lightweight dynamic-sized kernel CNN. Diagnostics, 12(9), 2048.

[20] Wang, Y., Wang, Y., Lee, T. K., & Miao, C. (2022). SSD-KD: A self-supervised diverse knowledge-distillation method for lightweight skin lesion classification using dermoscopic images.

[21] Griffith, V., & Foy, V. (2025). Teledermatology as a Solution for Rural and Rare Dermatologic Care: A Review of Strategies and Opportunities. Dermatological Reviews, 6(4), e70049.

[22] Fan, K., Liu, W., Miao, Y., Li, Z., & Liu, G. (2023). Engineering Strategies for Advancing Optical Signal Outputs in Smartphone‐Enabled Point‐of‐Care Diagnostics. Advanced Intelligent Systems, 5(6), 2200285.