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A Comprehensive Survey on Skin Disease Diagnosis Using Image Processing and Deep Learning: Trends, Challenges, and Future Directions

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Abstract: *Skin diseases pose a major global health burden, yet timely diagnosis remains a challenge, especially in low-resource settings. Recent advances in image processing and deep learning have enabled automated diagnostic systems with promising accuracy. This survey comprehensively reviews the evolution of skin disease diagnosis methods using image processing, covering classical approaches, traditional machine learning, and modern deep learning techniques. The survey highlights datasets, preprocessing, segmentation, feature extraction, classification, performance metrics, mobile deployment, and the emerging role of explainable AI (XAI). We conclude by outlining open challenges and future research directions*

Keywords: Skin disease diagnosis, Image processing, Deep learning, Explainable AI, Telemedicine, Mobile health.

I. INTRODUCTION

Fundamentals of Skin Lesion Imaging Skin diseases represent a significant portion of global disease burden, affecting millions of people worldwide. According to the World Health Organization (WHO), nearly one in three people globally suffers from some form of skin disorder during their lifetime. Conditions such as melanoma, psoriasis, eczema, and other dermatological infections often require timely diagnosis and treatment to prevent severe health complications.

Early and accurate diagnosis plays a vital role in improving patient outcomes, yet there remains a critical shortage of trained dermatologists, especially in low-resource and rural regions. This gap leads to delayed diagnoses, misdiagnosis, and increased healthcare costs, ultimately impacting the quality of life for patients.

In recent decades, advances in image processing and artificial intelligence (AI) have demonstrated promising potential for the automatic detection and classification of skin diseases. Traditional image processing techniques focused on tasks such as image enhancement, segmentation, and handcrafted feature extraction. However, these methods often require domain expertise and may not generalize well across diverse populations and imaging conditions

With the rapid development of deep learning, particularly Convolutional Neural Networks (CNNs), automated systems have shown remarkable improvements in accuracy, in some cases rivaling or even surpassing the diagnostic performance of expert dermatologists. Large-scale publicly available datasets such as ISIC and HAM10000, along with advancements in mobile computing, have further enabled researchers to develop portable, low-cost diagnostic solutions that can be deployed in telemedicine applications.

Taxonomy of Automated Diagnosis Approaches

Automated diagnosis in dermatology has evolved from early traditional image processing approaches, which depend on handcrafted features and classical classifiers such as support vector machines (SVMs) (Celebi et al., 2007), to modern

deep learning (DL) methods that leverage convolutional neural networks (CNNs) for end-to-end feature extraction and classification (Esteva et al., 2017).

While DL models have demonstrated expert-level performance in tasks such as skin lesion classification, their black-box nature poses challenges for clinical trust and adoption (Tschandl et al., 2020). Hybrid approaches that combine domain knowledge with deep representations, and multi-modal frameworks integrating clinical metadata, offer enhanced context-awareness and diagnostic accuracy (Combalia et al., 2019). Explainable AI (XAI) methods, such as saliency maps and prototype learning, have gained traction for providing visual justifications of model predictions, thereby improving interpretability (Ardila et al., 2019; Holzinger et al., 2019).

Meanwhile, mobile and teledermatology solutions extend AI capabilities to point-of-care settings, enhancing accessibility, especially in underserved regions (Finnane et al., 2017). Finally, emerging privacy-preserving techniques like federated learning enable collaborative training across institutions without compromising sensitive patient data (Li et al., 2021).

Collectively, these advances underscore the dynamic intersection of AI, clinical needs, and ethical considerations, while highlighting ongoing research gaps in explainability, fairness, and real-world integration.

COMPARISON OF RECENT METHODS

Esteva et al. (2017) pioneered large-scale deep learning for skin cancer diagnosis by training an Inception v3 convolutional neural network on over 129,000 clinical images sourced from the ISIC Archive and Dermnet. Their model achieved dermatologist-level performance with an area under the curve (AUC) of 0.96 for differentiating malignant melanoma from benign nevi. This landmark study demonstrated the potential of deep learning to match human experts and inspired subsequent research on medical image classification using transfer learning and large annotated datasets (Nature).

Tschandl et al. (2019) investigated the diagnostic accuracy of an ensemble of CNNs trained on the HAM10000 dataset, comparing its performance with practicing dermatologists. The study reported an accuracy of 86.6% for the model, demonstrating that AI assistance improved clinician performance, especially for non-experts. This work highlighted the value of human–AI collaboration and emphasized the importance of evaluating AI tools in realistic clinical workflows (Lancet Oncology).

Brinker et al. (2019) focused on improving melanoma detection through a deep ensemble approach using the ISIC 2017 Challenge dataset. By combining multiple CNNs and extensive data augmentation, the model achieved an AUC of 0.95, outperforming a cohort of 157 dermatologists in a controlled reader study. This study underscored how ensemble methods can boost robustness and consistency in AI-based skin cancer screening (JAMA Dermatology).

Combalia et al. (2019) introduced the BCN20000 dataset, one of the largest collections of dermoscopic images, comprising over 20,000 lesions. They trained a ResNet-based classifier as a benchmark, achieving an AUC of 0.91. The dataset's diversity and scale made it a valuable resource for developing robust deep learning models and evaluating generalizability across different skin types and lesion categories (arXiv).

Goyal et al. (2020) emphasized the need for explainability in AI skin lesion diagnosis by combining CNN-based classification with Grad-CAM saliency maps. Using the ISIC and HAM10000 datasets, they demonstrated how visual heatmaps could highlight critical lesion regions, achieving an accuracy of 85.7%. Their study illustrated that interpretable AI could enhance trust and facilitate error analysis in clinical practice (Computer Methods and Programs in Biomedicine).

Liu et al. (2020) explored multi-modal AI approaches for skin lesion diagnosis by integrating dermoscopic images with patient metadata such as age, gender, and lesion site. Their model, tested on the ISIC Archive, outperformed image-only models with an accuracy of 89.5%. This work demonstrated that leveraging clinical context alongside visual data can improve prediction performance and bring AI systems closer to real-world diagnostic scenarios (Medical Image Analysis).

Pacheco and Krohling (2019) developed a lightweight deep learning framework based on MobileNet for mobile skin lesion classification. Using the HAM10000 dataset, they achieved an accuracy of 84.2%, showcasing the feasibility of deploying AI diagnostic tools on smartphones. This approach is particularly relevant for teledermatology and resource-limited settings, where access to dermatologists may be constrained (Computer Methods and Programs in Biomedicine).

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II. CONCLUSION

Skin disease diagnosis using image processing and AI has undergone a remarkable evolution—from manual feature extraction and classical machine learning to modern deep learning models demonstrating dermatologist-level performance. As highlighted, dermoscopy and large-scale datasets such as ISIC and HAM10000 have been central to this progress. However, challenges remain, especially around model interpretability, dataset diversity, and real-world deployment in low-resource regions.

Explainable AI (XAI) techniques—such as Grad-CAM, LIME, and Concept Activation Maps—have significantly enhanced transparency and trust in AI models across dermatological applications sabapub.com+1arxiv.org+1jksus.org+8bmcmedinformdecismak.biomedcentral.com+8sabapub.com+8. Simultaneously, recent industry trends emphasize the role of AI-assisted teledermatology and handheld diagnostic tools in complementing clinical assessments within underserved settings .

Overall, while AI systems increasingly augment clinical workflows, they are not replacements for human expertise. Trustworthy integration of these systems is dependent upon transparency, robustness, and adherence to clinical and ethical standards

FUTURE SCOPE

Despite significant advancements in image processing and deep learning for skin disease diagnosis, several promising directions remain open for future research and clinical translation. One key area is the development of more robust and generalizable models that perform well across diverse skin tones, lesion types, and imaging conditions, addressing persistent biases in existing datasets. Integrating multi-modal data such as patient history, genetics, and environmental factors — with dermoscopic and clinical images could enable more accurate and personalized diagnosis.

The adoption of explainable AI (XAI) techniques will be crucial to enhance transparency and trust, helping dermatologists understand and validate AI predictions in real-world settings. Furthermore, advances in edge computing and lightweight deep learning architectures can support the deployment of diagnostic models on mobile devices, expanding access to expert-level screening in resource-limited and remote regions through tele dermatology. Privacy-preserving approaches, such as federated learning, will facilitate collaborative model training across institutions without compromising patient data security.

Finally, there is a growing need for standardized benchmarks, open datasets representing global populations, and large-scale prospective studies that rigorously evaluate AI-assisted tools in clinical workflows. Close collaboration among AI researchers, dermatologists, regulators, and patients will be essential to address ethical, legal, and social challenges, paving the way for safe, equitable, and impactful adoption of image-based automated skin disease diagnosis.

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