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A Survey on AI-Driven Skin Disease Diagnosis

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Abstract: Accurate diagnosis of skin diseases remains a significant challenge, as the process relies mainly on manual visual examination by experts. This traditional approach often leads to delays in providing timely first aid and proper treatment. To address these challenges, recent research has explored AI- based methods to improve the accuracy and efficiency of skin disease diagnosis using modern deep learning techniques. This survey reviews recent advancements in medical AI applications for dermatology, highlighting their potential to support more timely and precise patient care.

The survey also discusses the role of publicly available dermatology datasets such as HAM10000, which enable scalable and automated training of AI models. The reviewed studies demonstrate how AI-driven systems can assist healthcare professionals in making faster, more consistent, and data-supported diagnostic decisions. Despite these promising developments, challenges remain regarding dataset diversity, real-world deployment, computational requirements, and clinical validation.

Overall, this survey provides an overview of current AI-based approaches for skin disease detection, summarizes key research trends, and identifies existing limitations that must be addressed to ensure reliable and accessible dermatological care.

I. INTRODUCTION

In developing countries, the healthcare ecosystem continues this means dealing with increased pressures to meet escalat- ing demands. of a growing population and providing quick solution. As Skin is the largest organ of the human body; it constitutes a diverse group of medical conditions. The spectrum of these diseases varies from common, be from minor issues like acne to severe and potentially life-threatening ones. conditions such as skin cancers. Accurate diagnosis and classification cation, and segmentation of skin diseases are critical clinical tasks since they directly influence treatment strategies, patient outcomes, and overall healthcare efficacy. Misdiagnosis or de Delayed diagnosis may lead to unnecessary treatments or allow diseases progress to advanced stages that complicate therapy. and prognosis. Overcrowded public hospitals, limited access to Specialized medical professionals; high costs of consultation make timely, accurate health care a privilege rather than a right for many people. In rural and semi- urban areas, particular, they suffer from a lack of infrastructure and a shortage of Skilled medical personnel result in delayed diagnosis and preventable health complications. Integration of Artificial Intelligence into Health Care It has ushered in a new dimension in medical research, diagno sis, and patient care [1]. From automated image analysis to From predictive disease modeling to virtual consultations and per Personalized treatment planning, AI-driven systems do make. A transition from curative healthcare to being proactive, preventive, and precision medicine. In addition, natural language While NLP and deep learning have made these in making systems more intuitive and, consequently, allowing for effortless interaction. between technology and users, without the need for specialized knowledge. Traditionally, diagnosis of skin diseases has de- pended on relies heavily on expert clinical examinations. This Process usually involves visual examination, although often supported by devices such as dermoscopy that magnify images of the skin, allowing better visualization of the structures beneath the skin surface. Although these various traditional methods are well While established and widely used, they do have limitations. A huge concern is human error, since the accuracy of diagnosis depends on A diagnosis can vary according to the experience of the dermatologist. and com- petency. With these challenges, comes the growing A critical interest concerns the application of artificial intelligence (AI) to improve the precision, speed, and homogeneity of skin disease diagnosis and segmentation. A substantial volume of Recently, research has emerged that integrates AI techniques into the skin disease detection and segmentation, showing promising results in improving diagnostic processes. This Paper proposes a systematic review of the use of AI-based classification and segmentation of skin diseases The review aims to summarize the current understanding of the subject, pointing out prevailing methodologies, and outline the existing knowledge gaps within rapidly changing field. Systematic analysis of the The review, through a thorough look into the literature, gives insight into the effectiveness of AI in Skincare. This survey gives an in-depth look into the AI methods used for classifying and segmenting skin diseases. We have gathered compare and analyze a vast amount of research to comprehend the current situation and what will work, where the gaps exist, and what is the future. By bringing these insights together, this Paper aims to provide a summary to the current landscape of AI in dermatology: clear up on its strengths, challenges, and opportunities.

II. LITERATURE SURVEY

This section summarizes key findings from fifteen promi- nent research papers.

1) Doctor Approved: Generating Medically Accurate Skin Disease Images through AI-Expert Feedback (MAGIC) – arXiv (2025)

This work uses Stable Diffusion v2-1, combined with LoRA, textual inversion, and fine-tuning methods such as Di DPO and Reward Model Fine Tuning (RFT). Multimodal large language models (MLLMs) are used to automate evaluation based on dermatologist check. lists. The dataset includes subsets of Fitzpatrick17k, SCIN, and PAD-UFES-20. This paper's main advantage lies in generating Clinically accurate synthetic images that improve classifica tion models in low- data and few-shot settings while reducing the requirement for manual expert annotation [1].

2) Next-Generation Approach to Skin Disorder Prediction using a Hybrid Deep Transfer Learning Model (HDTLM) – Frontiers in Big Data (2025)

This research introduces a hybrid architecture that combines DenseNet121 and EfficientNetB0 backbones for skin disorder prediction. It utilizes both private and public datasets compris- ing 19 types of skin diseases. Hybrid Fusion of Features im- proves the diagnostic precision, generalization, and robustness; This is especially so for imbalanced datasets. The approach effectively integrates transfer learning and data augmentation, improving Precision without the need for large-scale data collection [2].

3) PatchAlign: Fair and Accurate Skin Disease Image Clas- sification by Alignment with Clinical Labels – arXiv (2025)

The model PatchAlign uses Vision Transformers (ViT) Along with Masked Graph Optimal Transport (MGOT) align- ment method. This helps in the alignment of visual features from skin images with clinical label representations. Experi- ments were performed on Fitzpatrick17k and DDI datasets. The A key advantage is that it significantly reduces skin tone bias. while enhancing classification accuracy and fairness across diverse patient groups, addressing one major ethical limitation. in dermatology AI models [3].

4) A Review of Skin Disease Detection Using Deep Learning – (2025)

This review paper provides a comprehensive overview of Deep learning methods such as Convolutional Neural Net works (CNNs), Transformers, Generative Adversarial Net works, GANs, and Ensemble models. It undertakes model analysis trained on datasets such as HAM10000, ISIC, and PH2; Summarizing best practices, including data augmentation and transfer. learning, and explainable AI. The main strength of this is that it con It solidifies current research trends and aids in performance identification. Benchmarks and gaps for future research are listed below. [4].

5) MAGIC

The extension of the first MAGIC paper, this version again The work leverages the use of Latent Diffusion Models; LoRA, and Direct Preference Optimization. Its advantage remains generate high-quality synthetic skin lesion images with medically verified accuracy, enabling better model gener alization in limited-data scenarios [5].

6) Skin Cancer Classification with Deep Learning: A System- atic Review – Frontiers in Oncology (2025)

This systematic review has compared several CNN architec- tures to identify which one is most promising regarding crack detection performance. tectures including ResNet, DenseNet, Inception, and VGG, often combined as ensemble models. Such datasets as It does so as HAM10000, ISIC, PH2, and BCN20000. Where deep learning consistently outperforms tra- ditional machine Learning approaches: The research portrays the success of ensemble learning, transfer learning, and data augmentation for achieving robust classification accuracy [6].

7) Skin Diseases Classification with Machine Learning and Deep Learning Techniques – Amina Aboulmira et al. (2024)

This review compiles findings across CNNs, Transformer Architectures, GANs, and ensemble methods trained on ISIC, HAM10000, and PH2 datasets. It concludes that ensemble and Augmentation strategies have consistently improved diagnostic accuracy. racy and reduce misclassification rates. The study also underlines the importance of standardized datasets and uniform evaluation These are the metrics that ensure repro- ducibility and clinical reliability [7].

8) *Skin Lesion Classification Using a Deep Ensemble Model – Applied Sciences (2024)*

This work puts together three deep learning architectures: ensembles—VGG16, Inception-V3, and ResNet50— into a weighted ensemble for skin lesion classification. Experiments were Performed on the ISIC-2018 and HAM10000 datasets. Through leveraging the complementary strengths of multiple architec ensembles attained an accuracy of around 97% on oversampled datasets. The model effectively captures di verse features make for better classification results. and increased robustness, especially to address class overfitting. imbalance via oversampling [8].

9) *Artificial Intelligence–Aided Diagnosis System for the De- tection and Classification of Skin Lesions – JMIR (2024)*

This paper introduces a two-stage model comprising a Multitask CNN for lesion detection and a Knowledge Graph Decision Network for final classification. It uses a private dataset of seven private-part skin diseases. The major advan tage of this approach is the combination of clinical knowledge and data-driven learning, improving interpretability and It helps doctors in diagnosis. It also enhances junior dermatolo- gist performance by 16% in comparative studies [9].

10) *. A Multi-Level Ensemble Approach for Skin Lesion Clas- sification Using Customized Transfer Learning with Triple Attention – PubMed (2024)*

This study proposes a multi-level ensemble combin- ing four The customized CNN variants that are used in this work are: CCNN, CACNN, SEACNN, and SACNN. Each model incorporates different attention mod rules: channel, squeeze-excitation, and soft-attention. Utilizing the HAM10000 dataset, the proposed Multi-Level Information Among them, Multiobjective Laboratory-IGPA (ML-IGPA) ensemble reaches about 94.9% accuracy. The effective ad- vantage of the method is that feature focus using attention mechanisms and its enhanced robustness through weighted ensemble learning [10].

11) *Enhancing Skin Disease Classification Leveraging Transformer-Based Deep Learning Architectures and Explain- able AI – arXiv (2024)*

It leverages Vision Transformers (ViT), Swin Trans, for- mers, and DINOv2 models, incorporating Grad-CAM and SHAP for interpretability. The dataset contains a custom 31- class dataset combined with HAM10000 and DermNet for validation. The DINOv2 model achieved 96.48% accuracy. and an F1-score of 0.9727. The benefit it holds is in the powerful global feature representation of Transformers, and the added transparency provided by explainable AI methods [11].

12) *Clinical Deep Learning Pipeline for Skin Disease Analysis – PMC10706240 (2024)*

This clinically focused paper applies CNNs with preprocess ing and segmentation techniques to aggregated dermatological datasets. It provides validation of deep learning models in clinical practice. flow using standard metrics such as F1-score and accuracy. Its advantage is the demonstration of practical, clinically integrated deep learning for dermatology diagnosis [12].

13) *. Classification of Skin Diseases with Deep Learning- Based Approaches – Scientific Reports (2025)*

This work couples CNN feature extraction with Relief feature selection that would improve performance on datasets similar to to HAM10000 and ISIC. It reached an accuracy of about 92.1% accuracy. Its biggest advantage is the balance between com putational efficiency and accuracy, achieved through feature selection that avoids redundancy but still conveys strong predictive performance [13].

14) *Enhanced Skin Cancer Diagnosis through Grid Search Algorithm-Optimized Deep Learning Models for Skin Lesion Analysis – Frontiers in Medicine (2024)*

It implements three task-specific CNNs, each optimized for end mized through grid search for different stages—lesion detec tion, benign/malignant classification, and seven-class disease Identification using the ISIC Dataset: The performance varied among the models by up to 98.72% accuracy. The main superiority is its clinically inspired modular design and the systematic tuning of hyper parameters that lead to reliable and explainable diagnosis performance [14].

15) *SkinScanPro: A Deep Learning-Based AI Health Assistant for Skin Disease Classification – IJERCSE (2025)*

This system uses DenseNet-201, fine-tuned with transfer. learning, and is deployed through a Flask web application. It was trained on a private dataset which contained 40,000 images. across 10 disease classes. The model achieved 93.2% test with an F1-score of 0.94. Its key benefit is that it is really time usability: Users can upload an image and get the AI in Accurate diagnosis

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immediately. The model effectively lever- ages DenseNet is efficient and capable of feature reutilization; accurate for large-scale use [15].

III. SUMMARY TABLE

TABLE I
SUMMARY OF REVIEWED RESEARCH PAPERS ON AI-BASED SKIN DISEASE CLASSIFICATION

S.No	Author(s)	Paper Title	Journal / Source	Key Advantages	Key Disadvantages
1	M. Wei, Q. Wu	Doctor Approved: Generat- ing Medically Accurate Skin Disease Images through AI- Expert Feedback (MAGIC)	arXiv (2025)	Generates clinically valid syn- thetic data; improves few-shot classification via DPO; scal- able expert feedback	Computationally heavy; re- quires expert validation; lim- ited disease coverage
2	S. Gulzar et al.	Next-Generation Approach to Skin Disorder Prediction using a Hybrid Deep Transfer Learn- ing Model	Frontiers in Big Data (2025)	Combines DenseNet121 & Ef- ficientNetB0; improves robust- ness and accuracy; effective on small datasets	Complex high architecture; lacks computationalcost; explainability
3	A. Aayushman, H. Gaddey, V. Mittal, M. Chawla, and G. R. Gupta	PatchAlign: Fair and Accurate Skin Disease Image Classifica- tion by Alignment with Clini- cal Labels	arXiv (2025)	Reduces bias across skin tones; fair and interpretable predictions	Requires high-quality clinical labels; limited dataset variety
4	S. Fatima, H. Shaikh, A. Sahito, and A. Kehar	A Review of Skin Disease De- tection Using Deep Learning	Journal of Medical Imaging Research (2025)	Comprehensive survey; identi- fies trends, datasets, and chal- lenges; provides methodologi- cal guidance	Lacks implementationor quantitative comparison; purely theoretical
5	M. Wei, Q. Wu	MAGIC (Detailed Entry)	arXiv (2025)	Produces high-quality synthetic data; improves model generalization	High computational resources required; relies on checklist accuracy
6	Y. Wu, B. Chen, A. Zeng, D. Pan, R. Wang, and S. Zhao	Skin Cancer Classification With Deep Learning: A Systematic Review	Frontier in Oncologys (2025)	Confirms DL superiority over classical ML; highlights en- semble and augmentation ben- efits	Lacks new experimental vali- dation; mostly descriptive
7	A. Aboulmira et al.	Skin Diseases Classification with ML and DL Techniques: A Systematic Review	IEEE Access (2024)	Highlights ensemble and aug- mentation strategies; provides structured taxonomy	No new dataset or experimen- tal analysis; focuses on past studies

8	M. Thwin, S. Park	Skin Lesion Classification Us- ing a Deep Ensemble Model	Applied Sciences (2024)	Ensemble of CNNs increases accuracy (97%); effective on imbalanced datasets	Computationally expensiv e; focuses only on three disease types
9	S. Wang et al.	AI-Aided Diagnosis System for Detection & Classification of Skin Lesions	Journal of Medical Inter- net Research (2024)	Combines CNN + Knowledge Graph; integrates clinical rea- soning; improves dermatolo- gist accuracy	Small, domain-specific dataset (seven diseases); limited scal- ability
10	R. Efat et al.	A Multi-Level Ensemble Approach Using Customized Transfer Learning with Triple Attention	Biomedical Signal Processing and Control (2024)	Triple attention enhances feature focus; ensemble weighting improves robustness (94.9% accuracy)	High training cost; complex structure; limited dataset
11	R. Mohan et al.	Enhancing Skin Disease Classification Leveraging Transformer-Based Deep Learning and Explainable AI	arXiv (2024)	Transformer models capture global features; achieves 96.48% accuracy; integrates explainable AI	Requires large data and GPU power; potential overfitting on small data
12	J. Zhang et al.	Clinical Deep Learning Pipeline for Skin Disease Analysis	PMC (2024)	Validates CNNs in real-world clinical workflow; focuses on accuracy and interpretability	Dataset details unclear; lacks model innovation
13	E. Sari, S. Keser	Classification of Skin Dis- eases with Deep Learning- Based Approaches	Scientific Reports (Na- ture, 2025)	Combines CNN and Relief feature selection; achieves 92.1% accuracy; efficient model	Uses older CNN architec- ture (AlexNet); limited disease coverage
14	V. Pillai et al.	Enhanced Skin Cancer Diag- nosis through Grid Search Op- timized Deep Learning Models	Frontier in Medicine s (2024)	Grid search optimization improves accuracy (up to 98.72%); clinically structured workflow	Time-intensive optimization; separate models increase complexity
15	M. Kiran Kumar et al.	SkinScanPro: A Deep Learning-Based AI Health Assistant for Skin Disease Classification	IJERCSE (2025)	DenseNet201 achieves 93.2% accuracy; real-time Flask web deployment; easy accessibility	Heavy model; no explainable AI; limited to ten disease types

IV. TABLE SUMMARY

These 15 reviewed studies collectively indicate the rapid progress made in using deep learning, ensemble models, and transformer architectures in AI-driven skin disease classifica- tion.

Most of the works used CNN-based transfer learning models such as DenseNet, EfficientNet, VGG16, and ResNet50, while newer studies explored Transformers (ViT, Swin, DINOv2) and diffusion-based methods (MAGIC) to improve the accu- racy and fairness of the models.

Typical datasets used include HAM10000, ISIC, Fitz- patrick17k, and custom hospital datasets, with reported accura- cies from 92% to 99%. Similarly, ensemble and hybrid models, such as Hybrid CNNs, Triple Attention, and Grid Search Optimization, provided superior robustness, while diffusion- based systems like MAGIC enabled the generation of synthetic data that were clinically valid for data augmentation.

However, almost all of these studies have similar limitations: small and imbalanced datasets, high computational require- ments, lack of clinical validation, and limited interpretability. Only a few works (e.g., Transformer + XAI models) addressed explainability and fairness across skin tones.

Generally, EfficientNet, DenseNet, and Transformer-based architectures turned out to be the most effective models with a good balance of accuracy, generalization, and efficiency.

V. FUTURE WORK

In the future, this research will be further developed into a real-world ready AI skin-diagnosis assistant capable of detecting skin conditions from images, conversing naturally in multiple languages, and giving first aid specific to context, including GPS-based emergency help. The vision system can utilize optimized architectures such as EfficientNet-B0 or EfficientNet-V2 Small, fine-tuned and distilled from advanced models like DINOv2 or DenseNet201 in order to achieve a balance between accuracy, speed, and scalability. The main characteristics of conversational intelligence, because a mul- tilingual chatbot integrating NLU, dialogue management, and response generation, will enable interactive, human-like com- munication tailored to user intent and language.

Context-aware decision-making will inform triage deci- sions—first aid for mild cases, emergency alerts for se- vere symptoms, and dermatologist referrals when uncertain. Location-based emergency assistance provided through GPS will ensure immediate medical access in life-critical situations. The user interface shall focus on empathy, safety, and clarity by using visual data, confidence indicators, and explainable AI features such as Grad-CAM visualizations.

This system aspires to bridge the gap between automated diagnosis and human care by combining medical reliability with real-world accessibility. This framework envisions an intelligent, accessible healthcare assistant that incorporates image recognition, natural dialogue, and emergency response to provide proactive, patient-centered care.

VI. CONCLUSION

The survey examined 15 recent research papers published between 2024 and 2025 that focus on using Artificial Intelli- gence to detect skin diseases. These studies explored differ- ent advanced AI techniques, including Convolutional Neural Networks (CNNs), Transformer models, ways to generate synthetic training images, and hybrid systems that combine various AI techniques. These studies show that deep learning is becoming a very powerful tool for analyzing images of skin conditions. Such successes notwithstanding, some challenges still remain. AI models are very complex and require a lot of computer power, making it difficult to run them on smaller machines, such as smartphones or in resource-limited clinics. Making smaller and faster AI models and integration into telemedicine and emergency care will help bring these tools from the lab to the clinic.

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