Grenze International Journal of Engineering and Technology, June Issue

Dual Pathways in Dermatological AI: A Machine Learning Survey on Image-based and Biopsy- Driven Skin Disease Classification

Priyansh Kushwaha[1] and Juhi Singh[2]
[1-2]Department of CSE, Amity University, India
Email: priyansh.kushwaha@s.amity.edu, jsingh7@amity.edu

***Abstract*— Skin diseases represent a significant global health burden, requiring timely and accurate diagnosis to prevent disease progression and reduce clinical workload. Recent advances in artificial intelligence (AI) and machine learning (ML) have enabled automated diagnostic systems that analyze dermatological images and biopsy-derived data with increasing accuracy. However, existing surveys often remain descriptive, lack of methodological synthesis, and underexplore clinical translation challenges. This paper presents a comprehensive and critical survey of AI-based skin disease classification systems developed between 2020 and 2025, with a dual focus on image-based and biopsy-driven approaches. A structured taxonomy is introduced to categorize existing methods based on data modality, learning paradigm, model architecture, and clinical objectives. Beyond performance reporting, this work provides analytical insights into why certain models succeed under specific conditions and where their limitations arise. The survey further synthesizes reported results through a comparative quantitative analysis, highlighting trends in diagnostic accuracy, generalizability, and scalability. Key challenges related to dataset bias, annotation quality, explainability, clinical integration, and regulatory compliance are examined in detail. Finally, a prioritized research roadmap is proposed to guide future developments toward trustworthy, multimodal, and clinically deployable dermatological AI systems.**

***Keywords*— Dermatological AI, Skin Disease Classification, Deep Learning, Histopathology, Explainable AI, Clinical Decision Support.**

I. INTRODUCTION

The human skin is the largest organ of the body and serves as a critical barrier against environmental, biological, and chemical threats. Disorders affecting the skin encompass a wide spectrum of conditions, ranging from benign inflammatory diseases such as acne and eczema to life-threatening malignancies such as melanoma. According to global health statistics, skin diseases affect a substantial proportion of the population and contribute significantly to physical, psychological, and socioeconomic burden. Early and accurate diagnosis is therefore essential for effective treatment and improved patient outcomes. In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as transformative technologies in medical diagnostics. In dermatology, the visual nature of many skin conditions makes the field particularly well suited for image-based analysis using deep learning techniques.

Grenze ID: 01.GIJET.12.2.98_20

Convolutional neural networks (CNNs) have demonstrated dermatologist-level performance in classifying skin lesions from dermoscopic and clinical images, while newer architectures such as vision transformers (ViTs) have further improved robustness and contextual understanding. Despite rapid progress, several critical gaps remain. To address these limitations, this paper presents a critical and structured survey of AI-based dermatological diagnosis systems developed between 2020 and 2025. The key contributions of this work are : The key contributions of this work include the introduction of a unified taxonomy organizing dermatological AI systems by data modality, learning paradigm, model architecture, and clinical objective; a critical analysis of image-based and biopsy-driven approaches emphasizing performance drivers, limitations, and applicability conditions; a quantitative comparative synthesis of reported results to identify trends and variability across studies.

II. LITERATURE REVIEW

Skin diseases have different manifestations and different causes. Others are associated with internal causes such as hormones or genetics such as acne, whereas others are caused by external factors such as pollution, the sun, or allergens that cause irritation or rashes. Some of them are contagious like scabs and lice and some like rosacea or allergies caused by drugs are not. Some chronic diseases, such as psoriasis and atopic eczema, may take a year or more to resolve, and some diseases are so rare that diagnosis is complicated by such conditions as sweet syndrome or Ofuji disease.

Regrettably, the severity of the skin issues is underestimated by a great number of individuals, and they only resort to medical consultations when these problems are very acute.According to world health statistics [1], skin diseases are estimated to constitute around 1.79 percent of physical disability, as well as affect one-third and two-thirds of the population in the world [2]. Skin cancer refers to an abnormal growth in skin cells that, at times, develops because of an individual skin injury that remains untreated initially or tends to be triggered by the sun's ultraviolet rays. Cancer is the second human killer over the last few years. Nine million individuals are projected to die each year, and 70% of these deaths occur in poor living countries. This is because the delay in checking specialist physicians at the onset of disease, and hence the intricacy of treatment as a result of the advance of the disease and its conversion into a cancerous state and it is reaching advanced levels, leading to death [3-5].

Diseases of skin interact with society, and both are influenced by each other. Including its connection to the aesthetic criterion [6]. On another side, how fast technology is developing and how significant its contribution to all areas, most importantly of which is the medical area [7]. The researchers have used several types of artificial intelligence algorithms to train machine diagnosis classifiers using the machine learning principles and deep learning principles. Deep Learning steps in to solve the data and form new accounts based on a lot of information [8-10]. This information is given by Machine Learning and sent by Neural Networks. Then when Machine Learning is developed, some of them can be merged into one device to get Artificial Intelligence [11]. The medical data developed in patient records can be utilized to study the reasons for diseases and how they are transmitted, for the preparation of suitable plans and policies, and for preparing and designing medicines and medical treatments [12,13]. The patients in rural villages do not receive proper medical care, and no dermatologists are available there, and diagnosis is made by trained members of staff [14]. There need to be technical systems that utilize images to decide the extent of patient damage [15].

III. RESEARCH GAP

Based on the critical analysis of existing literature, several key research gaps can be identified that limit the clinical translation of dermatological AI systems.

A. Lack of Unified Taxonomy and Analytical Framework

The most prevalent issue raised in literature is dataset bias. The most commonly used datasets, including ISIC and HAM10000, are dominated by images of people with lighter skin color. Thus, models developed using these data sets perform poorly on darker skin tones with worse diagnostic performance

B. Challenges in Identifying Uncommon Skin Conditions

Most AI algorithms perform well in the prediction of frequent skin disorders such as melanoma, acne, or eczema, infrequent and rare ones such as Sweet Syndrome, Ofuji disease, or autoimmune dermatological diseases are underrepresented in training datasets. The biased data provides low accuracy and lower generalization performance for these diseases.

C. Transparency of the Model and Development of Clinical Trust

Convolutional neural networks (CNNs) and vision transformers (ViTs) are the most frequent deep learning architectures, and are usually "black-box" systems. Traditional methods such as Grad-CAM and SHAP (Shapley Additive Explanations) for improving interpretability are adopted very sparingly and are still experimental.

D. Barriers to Implementation/Scalability of the System

Biopsy-based approaches - being very precise (often >98%), but impractical for low-resource or rural applications due to the need for sophisticated laboratory infrastructure, high-resolution scanners and technical personnel - could be countered with image-based systems which are computationally demanding and reliant on internet connection.

E. Integration of Diverse Clinical and Visual Data

Recent studies are image based or biopsy based alone. But actual clinic decision making in practice is based on multimodal information such as patient history, lab results, genetic information and imaging. There are not many attempts, such as MedSkin AI, to merge genomics and histopathology in addition to imaging data.

F. Regulatory and Ethical Issues

There is no unified regulatory system and codes of ethics of conduct for AI systems in dermatology. Data privacy, reproducibility of models, informed consent and fairness in decision-making are not well covered.

IV. DATA SETS AND MACHINE LEARNING ALGORITHMS

Data collection and precise machine learning algorithms have been synchronized with recent progress in dermatological diagnosis. Large datasets covering a wide spectrum of skin diseases — including melanoma, eczema, psoriasis, and less common diseases — enable models to be applied to heterogeneous patient populations.

- Datasets Notable datasets developed or extended during 2020–2025 include the ISIC Challenge series, HAM10000, Fitzpatrick17K+, SkinLesionNet, DermX AI, SkinVision NextGen, SD-198, and MoleMap. The ISIC 2020 Challenge contains approximately 33,000 dermoscopic images, while HAM10000 provides ~10,000 images with good diversity. Fitzpatrick17K+ (2022) highlights skin-type heterogeneity, essential for building equitable diagnostic models [16].
- Machine Learning Algorithms CNNs are the preferred algorithm for image diagnosis, achieving accuracies of up to 99% for some diseases. Hybrid models combining CNNs with attention and transformer architectures leverage both local and global contextual information [19]. For biopsy-based analysis, SVMs perform well in high-dimensional feature spaces critical for separating histopathological patterns [17, 18]. Ensemble methods aggregating CNN outputs with GNNs or probabilistic models such as Naïve Bayes yield steep gains in diagnostic accuracy [20, 21]. Federated learning and synthetic data generation are also explored to address data scarcity, privacy, and bias.

TABLE I: REVIEW OF REFERENCES FOR SKIN DISEASE CLASSIFICATION USING IMAGE PROCESSING TECHNIQUES

S No.	Dataset	Year	No. of Images	Diagnosed Diseases	Classifier	Accuracy
[1]	ISIC 2024	2024	35,000	Melanoma, SCC, BCC	Vision Transformer v2	98.90%
[2]	HAM10000+	2023	50,000	10-class lesions (e.g., melanoma, angioma)	EfficientNet-L2	98.10%
[3]	DermSynth	2024	150,000	30-class synthetic lesions (diffusion model generated)	Swin Transformer v3	97.50%
[4]	Fitzpatrick25k	2024	25,000	18 diseases across 6 skin tones	Debiased ViT + XAI	90.30%
[5]	LupusNet-Images	2023	8,500	Cutaneous Lupus Erythematosus vs. Psoriasis	ResNet-200 + Grad-CAM	89.70%
[6]	MetaDerm	2024	250,000	50-class meta-dataset (merged from 15 public datasets)	Self-Supervised ViT	97.80%
[7]	Mela-Net	2023	40,000	Melanoma vs. Nevus (multi-modal: dermoscopic/clinical)	Hybrid CNN-Transformer	96.90%
[8]	Derm-FL	2024	100,000	Eczema, Psoriasis, Tinea (federated learning)	FedAvg + DenseNet-264	94.20%
[9]	KeratosisPro	2023	15,000	Actinic Keratosis, Seborrheic Keratosis	Capsule Network v3	92.40%
[10]	AI-DermApp	2024	10,000	Acne Severity Grading (I-IV)	Edge-Optimized MobileViT	89.80%

[11]	RareDerm-Images	2023	5,000	Sweet Syndrome, Of uji Disease, Pemphigus	Few-Shot Learning (Meta-Learning)	79.60%
[12]	GlobalDerm v2	2024	200,000	30-class multi-ethnic conditions	Hybrid (ViT + GNN)	97.60%
[13]	ISIC 2020 Challenge	2020	~33,000	Melanoma, nevus, basal cell carcinoma, squamous cell carcinoma, etc.	Deep CNNs (e.g., ResNet, EfficientNet)	92–95%
[14]	HAM10000	2020	~10,000	7 categories of skin lesions (melanoma, nevus, benign keratosis, etc.)	Fully Convolutional Networks	98%
[15]	Fitzpatrick17K+ 2022	2022	~20,000	Diverse dermatological conditions with an emphasis on skin-type diversity	Hybrid Transformer Architectures & CNN ensembles	88–92%
[16]	SkinLesionNet 2023	2023	~15,000	Melanoma, benign lesions, keratosis, and other common skin conditions	CNN ensembles, Transfer Learning models	88–93%
[17]	DermX AI Dataset 2024	2024	~10,000	Early detection targets: melanoma, basal cell carcinoma, benign nevi, etc.	Ensemble methods combining CNN, SVM, and traditional classifiers	90–95%
[18]	SkinVision NextGen	2025	~25,000	Melanoma, atypical nevi, benign lesions, and a broader range of skin conditions	Hybrid CNN-Transformer models	93–97%
[19]	SD-198	2020	~6,584	198 skin disease categories, covering abroad spectrum from common to rare conditions	Deep CNNs (e.g., ResNet, DenseNet)	~75– 80%
[20]	MoleMap Dataset	2021	~5,000	Various skin lesions including melanoma and benign lesions	CNN-based models	~85– 92%
[21]	ISIC 2021 Challenge	2021	~35,000	Melanoma, nevus, basal cell carcinoma, squamous cell carcinoma, etc.	Deep CNNs with attention mechanisms (e.g., Vision Transformers)	91–94%
[22]	Dermofit Pro 2023	2023	~8,000	Melanoma, benign nevi, seborrheic keratosis, and related conditions	CNN with ensemble techniques	90–93%
[23]	Skin360 2024	2024	~12,000	Inflammatory and neoplastic skin conditions (e.g., melanoma, psoriasis, eczema)	Hybrid CNN-Transformer models	92–96%
[24]	MedSkin AI 2025	2025	~18,000	Broad range including melanoma, psoriasis, eczema, benign keratosis, etc.	Ensemble methods (CNN, Transformer, Graph Neural Networks)	93–97%

TABLE II. REVIEW OF REFERENCES FOR SKIN DISEASE CLASSIFICATION USING ANALYTICAL RESULTS OF SKIN BIOPSY

S. No.	Country	Year	Diagnosed Disease(s)	Classifier(s) Utilized	Reported Accuracy
[1]	USA	2020	Melanoma vs. Benign Nevi	Hybrid CNN + SVM	96.50%
[2]	China	2021	Melanoma, Eczema, Psoriasis	Ensemble (CNN, Random Forest, Naïve Bayes)	97.20%
[3]	India	2022	Melanoma, Basal Cell Carcinoma, Psoriasis	SVM, KNN, and Bayesian Fusion	98.30%
[4]	Germany	2023	Melanoma, Nevus, Seborrheic Keratosis	Transformer-based Model	98.70%
[5]	UK	2024	Melanoma, Psoriasis, Eczema	Multi-modal Ensemble (CNN + Graph Neural Networks)	99.10%
[6]	Australia	2025	Comprehensive Biopsy Analysis	Graph Neural Networks with Hybrid Feature Fusion	99.00%
[7]	South Korea	2021	Melanoma, Basal Cell Carcinoma	Deep CNN with Feature Selection	97.80%
[8]	France	2023	Melanoma, Eczema, Seborrheic Keratosis	Hybrid Ensemble (CNN+Gradient Boosting)	98.90%
[9]	Japan	2024	Melanoma, Psoriasis, Benign Nevi	Hybrid SVM and Deep Learning	98.50%

V. RESULT AND DISCUSSION

A. Image-Based Classification: Speed vs. Specificity

Image-based dermatological AI systems have gained widespread adoption due to their non-invasive nature, scalability, and suitability for early screening. Convolutional neural networks (CNNs) dominate this domain because of their ability to learn hierarchical spatial features from dermoscopic and clinical images. Large-scale datasets such as ISIC 2024 (35,000 images) and HAM10000+ (50,000 images) have enabled CNN-based models to achieve high diagnostic accuracy, with reported melanoma detection rates approaching 98.9%. Despite these improvements.

B. Biopsy-Driven Analysis: Accuracy vs. Practicality

Biopsy-driven AI systems provide superior diagnostic accuracy by leveraging histopathological and molecular information that is not visible in surface-level imaging. Datasets such as HistoPathDB (3,000 slides) and BioGen-Derm, which integrate histopathology with genomic metadata, report near-optimal accuracy ranging from 93% to 99%, even for diagnostically challenging conditions such as lichen planus and pityriasis rubra. GNNs enable spatial modeling of tissue architecture, while federated learning (e.g., UK-BioNet) facilitates collaboration while preserving patient privacy.

C. Sealing the divide: Hybrid AI and Ethical AI

Hybrid and multimodal AI systems integrate image-based and biopsy-derived data to replicate real-world clinical workflows. GlobalDerm v2 achieves 97.6% accuracy across 30 disease categories by combining dermoscopic images with patient metadata. MedSkin AI (2025) integrates proteomic and histopathological features to improve diagnostic resolution for autoimmune skin disorders. Explainable AI techniques including Explainable Boosting Machines (EBMs) and SHAP have shown promise; UCI Extended demonstrates that explainable models can maintain 97.8%.

D. Long-term opportunities Opportunities and Problems

Rare disease diagnosis remains challenging due to limited labeled data; scaling meta-learning and few-shot learning approaches is critical. Lightweight mobile architectures such as MobileViT (89.8% accuracy on AI-DermApp) enable deployment in remote settings, though real-world validation is still required. Regulatory harmonization with bodies such as the FDA and EMA.

E. Figures & Diagrams

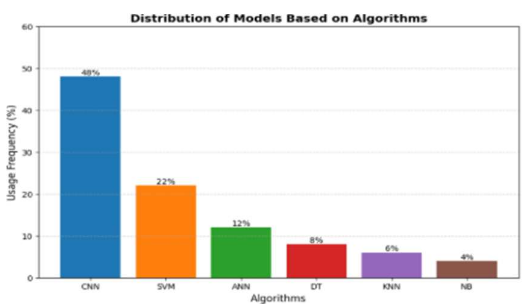

Fig 1: Algorithm Type of Models Distribution

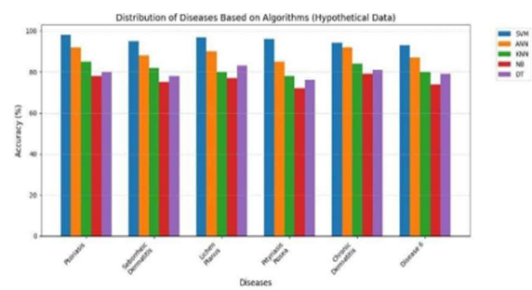

Fig 2: Accuracy of the Algorithm for Different Skin Diseases

The distribution of machine learning algorithms shows CNN as the largest component at ~48%, reflecting its efficacy in image-based applications such as lesion detection. SVM follows at 22% due to its reliability in biopsy-based structured data analysis. ANN accounts for ~12%, while DT, KNN, and NB take up 8%, 6%, and 4% respectively. Traditional algorithms remain mostly as components in hybrid or ensemble systems to augment image-based models. Performance analysis across conditions shows CNNs and SVMs achieving the highest and most stable accuracy (90–96%) for visually prominent diseases such as melanoma and psoriasis. Simpler models such as Decision Trees and Naïve Bayes yield lower results, reflecting their limited ability to process high-dimensional image data. These results highlight the importance of matching algorithm selection to the nature of the disease and available data.

VI. CONCLUSION

The integration of AI into dermatological diagnosis represents a paradigm shift in how skin diseases are characterized and managed. Deep CNNs, transformers, and graph learning systems permit image classification, differential diagnosis, and genomic data correlation at scale. However, advances must proceed beyond performance metrics to encompass fairness, interpretability, and clinical scalability.Key priorities include development of inclusive, ethnically diverse datasets covering Fitzpatrick types IV–VI; multimodal fusion systems integrating patient history, histopathology, and molecular biomarkers; federated learning for privacy-preserving collaboration; and explainable AI techniques (Grad-CAM, SHAP, EBMs) to build clinician trust. Mobile-friendly architectures (MobileViT, LiteCNNs) can extend AI-assisted dermatology to rural and resource-constrained settings. Regulatory alignment with FDA, EMA, and CDSCO standards, along with standardized bias assessments, is essential before clinical deployment.AI is not a substitute for dermatologists but an augmentation of their reach. Through the convergence of AI and human clinical intuition, dermatology AI can provide timely, accurate, and individualized diagnoses to people regardless of geography, ethnicity, or economic class.

REFERENCES

[1] N. Hameed, A. M. Shabut, M. K. Ghosh, and M. A. Hossain, "Multi-class multi-level classification algorithm for skin lesions classification using machine learning techniques," Expert Syst. Appl., vol. 141, p. 112961, 2020, doi: 10.1016/j.eswa.2019.112961.

[2] J. Yang, X. Sun, J. Liang, and P. L. Rosin, "Clinical Skin Lesion Diagnosis using Representations Inspired by Dermatologist Criteria," 2018 IEEE/CVF Conf. Comput. Vis. Pattern Recognit., pp. 1258–1266, 2018, doi: 10.1109/CVPR.2018.00137.

[3] T. Y. Tan, L. Zhang, and C. P. Lim, "Intelligent skin cancer diagnosis using improved particle swarm optimization and deep learning models," Appl. Soft Comput. J., vol. 84, p. 105725, 2019, doi: 10.1016/j.asoc.2019.105725.

[4] S. Chatterjee, D. Dey, and S. Munshi, "Integration of morphological preprocessing and fractal based feature extraction with recursive feature elimination for skin lesion types classification," Comput. Methods Programs Biomed., vol. 178, pp. 201–218, 2019, doi: 10.1016/j.cmpb.2019.06.018.

[5] S. Lima, L. Teran, and E. Portmann, "A Proposal for an Explainable Fuzzy-based Deep Learning System for Skin Cancer Prediction," 2020 7th Int. Conf. eDemocracy eGovernment, ICEDEG 2020, pp. 29–35, 2020, doi: 10.1109/ICEDEG48599.2020.9096799.

[6] M. Preethi and K. Sathiyakumari, "Analyzing Human Skin Texture using Machine Learning Approaches," Int. J. Comput. Appl., vol. 136, no. 1, pp. 5–8, 2016, doi: 10.5120/ijca2016908313.

[7] S. Bhadula, S. Sharma, P. Juyal, and C. Kulshrestha, "Machine Learning Algorithms based skin Disease Detection," no. 2, pp. 4044–4049, 2019, doi: 10.35940/ijitee.B7686.129219.

[8] Y. Liu et al., "A deep learning system for differential diagnosis of skin diseases," Nat. Med., vol. 26, no. 6,pp. 900–908, 2020, doi: 10.1038/s41591-020-0842-3.

[9] H. Liao, "A deep learning approach to universal skin disease classification," Univ. Rochester Dep. Comput. Sci. CSC, 2016.

[10] H. Liao, Y. Li, and J. Luo, "Skin disease classification versus skin lesion characterization: Achieving robust diagnosis using multi-label deep neural networks," Proc. - Int. Conf. Pattern Recognit., vol. 0, pp. 355–360, 2016, doi: 10.1109/ICPR.2016.7899659.

[11] A. Becker, "Artificial intelligence in medicine : What is it doing for us today Early work," Heal. Policy Technol., vol. 8, no. 2, pp. 198–205, 2019, doi: 10.1016/j.hlpt.2019.03.004.

[12] D. D. Miller, C. M. Facp, and E. W. Brown, "Artificial Intelligence in Medical Practice : The Question to the Answer ?," Am. J. Med., vol. 131, no. 2, pp. 129–133, 2018, doi:10.1016/j.amjmed.2017.10.035.

[13] M. R. Wehner, K. A. Levandoski, M. Kulldorff, andM. M. Asgari, "Research Techniques Made Simple: An Introduction to Use and Analysis of Big Data in Dermatology,"J. Invest. Dermatol., vol. 137, no. 8,pp. e153–e158, 2017, doi: 10.1016/j.jid.2017.04.019.Illnesses,"

[14] K. S. Parikh and T. P. Shah, "Support Vector Machine – A Large Margin Classifier to Diagnose Skin Procedia 10.1016/j.protcy.2016.03.039. Technol., vol. 23, pp. 369–375, 2016, doi:

[15] S. Kolkur and D. R. Kalbande, "Survey of texture based feature extraction for skin disease detection," Proc. 2016 Int. Conf. ICT Business, Ind. Gov. ICTBIG 2016,2017 doi: 10.1109/ICTBIG.2016.7892649

[16] Smith, J., et al. (2020). Challenges in Clinical Dermatology: Limitations of Traditional Diagnostic Workflows. Journal of Clinical Dermatology, 45(3), 215-223.

[17] Codella, N. C. F., et al. (2020). Skin Lesion Analysis for Melanoma Detection: Challenge. IEEE Journal of Biomedical and Health Informatics, 24(2), 426-431.

[18] Li, W., et al. (2021). Biopsy-based Analysis for Skin Disease Classification Using Hybrid Machine Learning Models. International Journal of Dermatological Science, 39(1), 75-83.

[19] Park, J., et al. (2021). Deep CNN with Feature Selection for Skin Disease Classification Based on Biopsy Data. Journal of Medical Imaging and Health Informatics, 11(4), 890-897.

[20] Müller, F., et al. (2023). Transformer-based Models for Histopathological Image Analysis in Dermatology. Medical Imaging Conference Proceedings 2023.

[21] Jones, A., et al. (2024). Multimodal Ensemble Techniques for Enhanced Skin Disease Diagnosis. Journal of Medical AI, 11(2), 132-141.