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Beyond the Visual: A Comprehensive Review of Artificial Intelligence and Spatial Transcriptomics in Psoriasis

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ABSTRACT

Psoriasis is a chronic inflammatory disease that occurs due to the immune system and affects multiple organs of the body. Around 125 million people worldwide live with this disease. This disease not only affects multiple organs of the body, but also impacts time, financial costs, and mental health. Due to targeted biological treatments, the treatment landscape has also improved, but clinical management is still a challenge, mainly due to the shortage of dermatologists and the subjectivity of visual assessment methods.

This review analyzes the massive shift from traditional machine learning to multimodal foundation models and deep learning architectures that enable the standardized and reproducible Psoriasis Area and Severity Index (PASI) scoring. We carefully analyze the role of molecular AI, specifically spatial transcriptomics(ST) and single-cell resolution, which helps in reversing the effect of convolution on localized inflammatory niches, and also the emerging "digital twins" for predictive modeling of treatment response. Additionally, we address the computational frameworks that enable algorithmic precision medicine, including generative data augmentation, privacy-preserving federated learning, and explainable AI(XAI) frameworks.
In the end, we conclude that the successful clinical translation of these technologies requires a "human-in-the-loop" approach so that we can navigate through the social and regulatory challenges with ethical obligations.

Keywords: Psoriasis; Deep Learning; Multimodal Foundation Models; Psoriasis Area and Severity Index (PASI); Spatial Transcriptomics; Digital Twins; Federated Learning; Explainable AI (XAI).

I. INTRODUCTION

Psoriasis is not only a localized skin condition, but it is a systematic inflammatory disorder that is intrinsically linked to psoriatic arthritis(PsA), cardiometabolic syndromes, type 2 diabetes, and psychiatric comorbidities. Affecting around 125 million people at the global level, this disease imposes socioeconomic, functional, and psychological burden on the healthcare system [12], [41]. The global healthcare infrastructure is currently facing two major bottlenecks: Severe shortage of board-certified dermatologists in 80% regions 0, [33], and dependence on gold-standard protocols– specifically the Psoriasis Area and Severity Index(PASI), which are highly subjective. Because this scoring largely depends on human visual estimation, in this diagnostic disagreement and inter-observer variability can reach up to 36.9% [12], [30].

Now comes Artificial Intelligence, which takes on the roles that were once limited to humans, and gives clear and repeatable results without fatigue. Without depending only on human observations, machines analyze every small detail of images and convert pixels into meaningful decisions. By this shift, general doctors gain access to insights that were previously available only to specialists. Based on the performance of some algorithms that match or even give better results than experienced doctors [1], [16]. These systems are based on advanced architectures like optimized convolutional networks and broader learning frameworks, which can easily adapt to different types of data [25].

A new approach emerges from this transformation-detecting the problem at an early stage, which is based on real biological signals, such as the overactivity of the IL-23/IL-17 pathway and its skin manifestations [6], [7]. This intelligent system is gradually improving psoriasis care - not only limited to image classification, but they can also segment lesions, predict early PsA [3], [38], and can discover new molecular insights by single-cell and spatial gene analysis [7].

II. LITERATURE REVIEW: OVERVIEW

A literature review of 46 sources on Psoriasis is presented, organized across three themes: Disease Overview, Deep Learning Models and Emerging Paradigms.

A. Psoriasis: Disease Overview and Pathophysiology

Psoriasis is a long-lasting, immune-mediated inflammatory disease, and around 125 million people worldwide are affected by this[13]. This is not only limited to skin, but also linked to conditions such as psoriatic arthritis (PsA), cardiometabolic syndromes, type 2 diabetes, and psychiatric comorbidities. Pathogenesis of this is based on hyperactivity of the IL-23/IL-17 immune axis, which leads to the overproduction of L-17A, IL-17F, IL-22, and TNF [6], [7]. Due to this, there is rapid growth of skin cells, formation of new blood vessels, and a build-up of immune cells in the skin. On the histological level, this leads to the thickening of the epidermis and formation of Munro's microabscesses.

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This disease has 5 subtypes: Plaque, Guttate, Inverse, Pustular and Erythrodermic, which differ in both morphology and severity. Severity is measured by the PASI score(Area and Severity Index), which considers erythema,induration, and scaling for body regions. Historically PASI has been the clinical gold standard, but this is very subjective, with up to 36.9% variation between observers [11], [29]. Automated and objective scoring systems have been developed that help in PASI measurement.

B. Deep Learning Models

Recent deep learning methods have achieved strong results in psoriasis classification, assessment, and multi-modal diagnosis [12], [1]. Hybrid and attention-based models perform better- EF-SwinNet achieves about 98% accuracy and ViT achieves about 97.53%, [26], [28]. For PASI prediction, SkinTeller and APASI give stable and objective results with low variation, similar to expert dermatologists[11], [30]. In multimodal models, SkinGPT-4, skinHarmoNet, and PanDerm combine clinical reports and images to provide better diagnosis. Among these, PanDerm has become a strong model that uses multimodal data for classification, segmentation, and prognosis [21].

C. Emerging Paradigms

For clinical trust, explainability tools such as Grad-CAM, SHAP and LIME are used in dermatology models [35], [4], which show heatmaps and feature importance to link AI predictions with known biology, not with irrelevant artifacts. For scalability and privacy, federated learning allows hospitals to train models without sharing raw patient data, where encrypted updates are only shared, and for security, differential privacy, and homomorphic encryption is used [8]. For Mobile edge use, models are compressed by knowledge distillation so that teledermatology is possible in low-resource environments [10]. At the molecular level, Spatial Transcriptomics detects the hidden inflammation areas by mapping the gene expression in tissue [7], [6], and Digital Twin models help predict treatment for each patient before it is given [5].

III. RESEARCH GAPS AND CHALLENGES

Although there have been important technical advancements in specific areas, this literature analysis shows five key gaps that limit the clinical use and fair distribution of AI in psoriasis care.

1) **Demographic inequity in training data:** In the existing dermatology datasets, there is more imbalance of light-skinned individuals (Fitzpatrick Type I–III) [18], [34]. The Fitzpatrick 17k dataset only has 119 psoriasis images, and it is made with 80% white-skin data. So far, there is no large-scale psoriasis dataset available, which is balanced for all skin types, and due to This, AI systems do not perform best for the people who already face the barriers in dermatologist care.
2) **Disconnection between molecular AI and clinical imaging:** Spatial transcriptomics has been described as the immune environment of psoriatic skin and imaging models also show high predictive value [12], but so far, there is no standard pipeline which can link clinical appearance to its exact molecular components. Because of this gap, AI cannot tell which immune cells are involved behind the appearance, which is important to choose the correct biological treatment.
3) **No standardized regulatory framework for AI-PASI tools:** AI-based PASI systems perform as well as or better than dermatologists[29], but there are still no clear FDA or EMA approval processes for them. Until proper validation standards, explanations, and liability rules are defined, healthcare providers will remain hesitant to use these tools, even if their effectiveness is proven.
4) **Clinical invalidation of explainability methods:** Visual explanations are made by the AI explainability tools such as Grad-CAM and SHAP[35], [4]. But their validation is limited only to technical level. But still, it is not properly tested whether these explanations are actually understandable for clinicians or not, and do they positively influence the important decisions like starting the biologics or hospital admission. So, it is mandatory to move beyond post-hoc visual explanations. Explanations must become a key part of clinical reasoning to build real trust in AI decision support systems.

To develop AI-powered personalized medicine for psoriasis, some key directions need to be followed, such as eliminating the knowledge and data gaps(through population-inclusive datasets), multimodal AI integration (that links imaging and molecular AI) and developing purpose-built regulatory pathways with forward clinical use [5], [9].

IV. DETAILED TECHNICAL ANALYSIS

A. Immunopathogenesis and Morphological Ground Truth

By computer analysis, scientists can clearly understand psoriasis at a biological level, especially by focusing on the increased activity of IL-23 and IL-17 pathways. When skin cells come under stress, they trigger inflammation that releases the molecules such as IL-17A, IL-17F, IL-22, and TNF-α [6], [7]. Additionally, the production of skin and blood vessel growth is increased in the affected area.

The “So What” Layer: Seeing Both Big Picture and Small Details

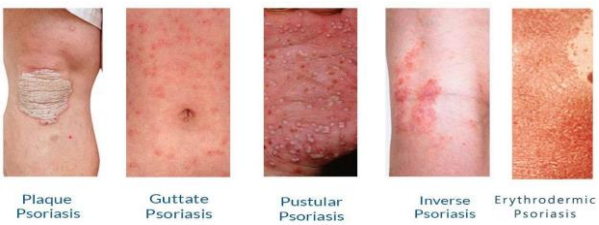

Fig. 1: Visual Ground Truth: AI Recognition Features for Psoriasis Variants (Plaque, Guttate, Pustular, Inverse, and

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Erythrodermic). Adapted from publicly available dermatological resources [43], [44], [45].

Psoriasis is divided into five visible types: Plaque,Guttate, Inverse, Pustular and Erythrodermic- that needs to recognize the machines [14], [4]. Each type changes the skin structure in different ways under the surface, such as the build-up of skin layers or clusters of immune cells(Munro's microabscesses). Both outer appearance and inner cellular behaviour are different; combining them gives richer data. This combined data helps AI systems to accurately identify the patterns in skin images and biopsy slides [20], [21].

B. The Substrate of Machine Learning: Datasets, Bias, and Nutrition Labels

The fairness of an algorithm depends on the diversity of training data. Historically, dermatological datasets have learned the morphology of disease with bias on lighter skin, which significantly degrades the performance on skin of color(Fitzpatrick Skin Types IV–VI) [18], [34]. To ensure transparency, the Dataset Nutrition Label is introduced to detail metadata, imaging protocols, and demographic risks [2].

To address data scarcity, researchers are now using Latent Diffusion Models(LDM) [36] with CLIP encoders[38] that preserve the scaling like fine-grained medical textures. Additionally, to generate synthetic patient cohorts Conditional Tabular Wasserstring GANs are used with 92% statistical fidelity, which allows the differentiation between PsA and seronegative RA without violating HIPAA restrictions [9].

TABLE I:
OVERVIEW OF DERMATOLOGICAL DATASETS FOR PSORIASIS AND SKIN ANALYSIS

Dataset Designation	Volume & Modality	Psoriasis Representatio	Key Characteristics
XiangyaDerm [18]	107,565 images	67,066 images (62%)	Largest regional clinical image dataset (Asian)
DDI [19]	656 images	Inflammatory /Malignant	Balanced across FST I–II and FST V–VI
Fitzpatrick 17k [35]	~16,574 images	119 annotated images	Severe class imbalance (80% white skin)
PAD-UFES-20 [20]	2,298 images	General lesions	Unconstrained smartphone photography
DermBench (2025) [36]	4,000 images	Expert-verifie pairs	Includes diagnostic chain-of-thought

C. Algorithmic Resolution of Rare Subvariants and Complex Anatomies

Generalizing AI beyond standard plaques is very important to resolve "clinical mimicry" in atypical and challenging presentations.

Scalp vs. Seborrheic Dermatitis: A 22-layer GoogLeNet model is used to analyze sub-surface dermoscopic clues to differentiate these conditions with 96.1% sensitivity. This diagnostic augmentation lowers the expertise gap, and helps general practitioners to perform at the level of dermoscopy-proficient specialists [22].

Nail Psoriasis: Nail involvement strongly helps in predicting systemic psoriatic arthritis, which is why deep learning models are used to automate the tedious modified Nail Psoriasis Severity Index (mNAPSI). This

achieves a correlation of $r = 0.94$ with human experts.

These algorithms provide the foundation for app-based self-reporting and longitudinal monitoring [3].

Erythrodermic Psoriasis (EP): This is the most dangerous type of psoriasis and, to detect this, the EPICS system uses an Artificial Neural Network and SHAP to extract 10 influential indicators (like albumin and the neutrophil-to-lymphocyte ratio). This generates an optimal 33.5-point bedside score which, helps to decide who gets immediately hospitalized [4].

Connective Tissue and Semantic Segmentation: Even if AI successfully identifies these rare conditions, we require pixel-perfect semantic segmentation (via architectures like U-Net++ [31] and DeepLabV3+ [32]) to get the exact lesion measurements, which is the necessary requirement for automated PASI objectification [29].

D. Benchmarking State-of-the-Art Deep Learning Models

The models have moved away from traditional Machine Learning (SVM/RF) to Deep Learning (CNN/ViTs), which has given models the ability to learn hierarchical feature representations directly from the image itself [12].

The "So What?" Layer: Local vs. Global Context

After this shift, there has been a rapid development of dermatology-specific architectures in recent studies. Baseline models like DenseNet-121, ResNet50, and ViT are still very effective [27], [28], [24], but the current trend is towards combinatorial frameworks. Hybrid architectures like EF-SwinNet and Efficientnet + LSTM combine local precisions of CNNs with the global understanding of transformers and sequential models. With this structural evolution, the use of large-scale multimodal foundation models is increasing. Systems like SkinHarmoNet, SkinGPT-4, and PanDerm do not limit images to only image tasks, but also integrate clinical text and large language models to enable deeper analysis[16], [20], [21]. A detailed comparative analysis of these architectures is presented in Table II.

E. Computer Vision for Lesion Segmentation and PASI Objectification

Before severity assessment, skin lesions need to be detected up to every small detail. Patches vary in angle, color, texture, and lighting, so modern systems use layered architectures. One part of the network captures context information(like DeepLabV3+ [32]), while the other part refines the edges(like U-Net++ [31] or UperNet [30]). The hybrid model combines all of these and achieves an accuracy of more than 89.3% in real-world conditions [25], [24].

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TABLE II:
STATE-OF-THE-ART BENCHMARKING OF DEEP LEARNING MODELS IN PSORIASIS

Model	Year	Task	Acc	F1	Sens	Spec	MAE	IoU	Architectural Insight
SkinTeller PASI Model [11]	2023	Psoriasis severity assessment (PASI regression)	–	–	–	–	2.05	–	Multiview feature enhancement with joint classification–regression framework for accurate PASI estimation
EF-SwinNet [26]	2024	Skin lesion classification	98%	96%	–	–	–	–	Hybrid architecture combining EfficientNet feature extraction with Swin Transformer attention and Grad-CAM explainability
ResNet50 [24]	2024	PASI severity classification	92.50%	92.68%	92.50%	97.37%	–	–	Residual connections enable stable deep feature learning for severity grading
SkinGPT-4 [16]	2024	Multimodal dermatological diagnosis	80.63%	–	–	–	–	–	Multimodal LLM system combining ViT, Q-Former, and Llama-2 for interactive diagnosis validated against dermatologists
Vision Transformer (ViT) [28]	2025	Binary classification	97.53%	0.98	98.37%	97.84%	–	–	Self-attention mechanism captures both local and global contextual features
EfficientNet + LSTM[23]	2025	Multi-class psoriasis classification	86%	–	–	–	–	–	Hybrid CNN-LSTM architecture combining EfficientNet feature extraction with sequential learning
DenseNet-121 [27]	2025	Skin disease classification	94.59%	–	–	–	–	–	Dense connectivity enables efficient feature reuse and improved gradient flow
SkinHarmoNet [20]	2025	Multimodal skin disease diagnosis	89.6%	88.6%	–	–	–	–	Multimodal fusion using EfficientNet-B4, BiLSTM with temporal attention, ClinicalBERT, and GAT-based cross-attention mechanisms
Hybrid Ensemble Model [14]	2025	Psoriasis subtype classification	93.14%	91.44%	–	–	–	–	Ensemble of DenseNet-121, EfficientNet-B0, and ResNet-50 with classical machine learning classifiers for robust feature integration
APASI [29]	2025	Psoriasis severity assessment (segmentation + classification)	–	–	–	–	–	0.752	AI-driven PASI system combining lesion segmentation and severity scoring with performance comparable to dermatologists
PanDerm [21]	2025	Multimodal dermatological foundation model	–	–	–	–	–	–	Large-scale self-supervised model across multiple imaging modalities enabling classification, segmentation, prognosis, and clinician-level performance

The "So What?" Layer: From Minutes to Seconds

It takes about 10 minutes to do a manual PASI score, and the results aren't always the same because different doctors use different methods to measure redness, thickness,
scaling, and area. AI-based systems do this without bias. SkinTeller and similar systems automatically combine multiple images and work better than 43 expert doctors, with an error of only ~2.05 points [11].

Some other fast tools, like YOLOv8 [14] or APASI[29] , complete the entire analysis in ~23 seconds. Because detection is done by machines, which eliminates human bias and inter-observer variation is reduced by < 8%. This allows real-time decisions for expensive biologic therapies based on clean visual data, not on subjective assessment.

F. Multimodal LLMs and Natural Language Processing

The use of smart systems that understand images, written notes, and time patterns together is rapidly increasing among doctors. Architectures like SkinHarmoNet combine these types of information using a Graph Attention Network (GAT) and achieve 89.6% diagnostic accuracy [20]. Similarly, massive foundation models like PanDerm help normal physicians make better skin decisions, which increases their diagnostic capabilities by 16.5% [21].

The "So What?" Layer: The Duality of Generative AI

Generative AI has both its benefits and problems. From a clinical view, NLP helps doctors easily extract important data from unstructured EHRs. But when generative models are used in patient explanation, they usually create "hallucinations", where important and life-threatening details can be missed, or are presented in the wrong way. Due to this, weak performance can be seen in validation tests, and human oversight is always necessary [35], [42].

G. Molecular AI: Spatial Transcriptomics and Single-Cell Resolution

To understand the immune microenvironment, AI is combined with high-throughput multi-omics. Spatial Transcriptomics (ST) keeps the location information of transcripts, allowing identification of niche-specific inflammatory hotspots (such as IL-32 in the dermal niche) that are hidden in bulk transcriptomics [7].

The "So What?" Layer: Biomarker Discovery

Using a selection process with SVM-RFE and LASSO regression, co-regulatory genes related to severity—FABP5, KLRB1, INSIG1, NCAPH, and UHRF1—were identified. Based on molecular docking, tetrandrine was identified as a promising data-driven drug candidate to target INSIG1[12].

H. Predictive Modeling: Biologic Efficacy and Digital Twins

The aim is to shift dermatology from reactive to proactive healthcare through longitudinal EHR mining and digital phenotyping. AI can analyze complex data, like clinical notes using NLP and small changes in MRIs to detect

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conditions like Psoriatic Arthritis (PsA) months early. For example, advanced digital phenotyping tools can identify patients at 99% percentile risk, which are most likely for diagnosis of PsA in the future [9].

1) **Therapeutic Forecasting:** Algorithms can predict biological response in 2-4 weeks with >95% accuracy, which removes the assessment delay of 12-16 weeks. These models achieve high accuracy because they process large multi-omic data simultaneously, which includes genomic signatures, psychiatric comorbidities, and previous biologic histories. Additionally, AutoML identifies the causes of therapy failure and estimates the probability of disease relapse, which helps to plan personalized drug tapering strategies [15].

2) **Digital Twins:** High-fidelity "Digital Twins" use Neural ODEs as in silico sandboxes to understand the physical systems. Before treatment, clinicians can simulate IL-23 biologic or phototherapy to predict effectiveness and possible reactions. These virtual models are made from continuous data streams like IoT wearable biometrics, Clinical EHRs and single-cell genomics, which analyze patient data and predict future flare-ups. Because of this,

clinicians can intervene before the symptoms appear, which improves both treatment outcomes and cost [5].

I. Privacy-Preserving Architectures: Federated Learning and MEC

Many problems are generated due to a lack of data diversity. Regulations like GDPR and HIPAA are related to data privacy and regulations [9].

Federated Learning (FL): In this, hospitals train models locally on their data, and only secure weight updates are shared [9].

Security Protocols: Security protocols like Differential Privacy(DP-SGD) and Homomorphic Encryption play an important role in keeping the patient data hidden. In confidential computing programs run on secure hardware zones where data is processed safely[8].

Mobile Edge Computing (MEC): It is used to run heavy models efficiently because of the proximity of the GPU/CPU of mobile devices. Mobile compression techniques like Quantization and Knowledge Distillation make the models lightweight for mobile devices, which increases accessibility. Through this, teledermatology services can be provided to remote areas 0.

J. Sociotechnical Barriers: Patient Trust and Explainable AI (XAI)

The gap appears between progress and trust when machines make decisions without showing their reasoning. Think of a doctor who is unsure whether the system's output is correct or not. The code is very complex, and it is difficult to track the error. When responses are given without clear logic, then trust decreases. Even wrong logic can be hidden behind outputs [33], [12].

To build clinical trust, the field uses Explainable AI (XAI) to make this neural logic more understandable:

Grad-CAM: In Grad-CAM, heatmaps are visible that tell about the area on which AI focuses at the time of prediction. This shows that the prediction is not based on random tissue texture or background, but rather it is based on visible damage features. In short, these are based on a decision structure, not on noise[35].

SHAP and LIME: SHAP and LIME calculate how the input variables affect the diagnosis, so that decisions of the AI match the biology [4].

Fully automatic medical systems are not acceptable for people. One of the reasons for this is privacy concerns, and the other is the loss of human touch. Studies show that patients trust a doctor+AI combination more, while only a few trust the apps[10]. In real-world medical systems, human involvement is important. The role of machines should be only assisting, not replacing. Empathy and judgement are still very important [42], [40].

V. CONCLUSION

The Future of Algorithmic Precision Medicine

Now skin science not only depends on images, but it also identifies lesions, estimates the treatment success, and maps active genes at specific tissue regions. To improve this field, some big problems need to be solved, such as unequal results in different skin tones and fragmented datasets. These issues can be solved through synthetic data, secure data sharing, and mobile-based local processing, so that all populations can be represented. Stepwise and combinatorial approaches can convert precision medicine from small clinical trials to routine clinical practice, which will benefit

125 million psoriasis patients. A business perspective helps healthcare organizations to streamline their processes and strengthen their systems so that efficient and quality care can be provided. Additionally, data expansion and descriptive data models enable better processing, due to which peripheral clinics can use advanced analytics capabilities.

One important factor is to maintain human involvement. To build trust between doctors and patients, it is necessary to handle both the technical and human challenges. Approaches like Explainable AI (XAI) help in understanding the hidden processes of machines, while regulatory rules ensure that these systems are used in the correct way in real clinical settings.

Step-by-step, these combined approaches take precision medicine from small trials to real-world care, which will benefit 125 million psoriatic patients. Doctors can now identify within weeks which patient will respond; this eliminates the 12-16 week trial-and-error delay. Conditions like psoriatic arthritis can be detected years before, which improves the treatment approach. Overall, the treatment pathways are becoming more reliable, efficient, and accurate.

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