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Advancing Skin Cancer Diagnostics with Human-AI Synergy– A Review

Fatemeh Kouhestani
Department of Science, Technology, Engineering & Math, HCC, Houston, TX, USA
w216483953@student.hccs.edu

Abstract: *Skin cancer remains a major global health concern, with early and accurate diagnosis playing a vital role in improving outcomes and reducing healthcare burdens. In recent years, artificial intelligence (AI), particularly deep learning models such as convolutional neural networks, has emerged as a transformative tool in dermatology. This review critically examines five peer-reviewed studies published between 2022 and 2025 that explore AI's role in skin cancer detection, comparing its performance to clinicians, evaluating human-AI collaboration, and assessing advances in multimodal and explainable systems. The findings highlight AI's growing diagnostic precision, especially in aiding non-specialist providers and improving access in underserved regions. However, challenges such as data bias, limited diversity, and the lack of interpretability in AI models remain pressing. By synthesizing evidence from multiple perspectives, this article underscores the importance of ethical, transparent, and clinically validated AI integration. Ultimately, AI should be viewed not as a replacement for medical expertise but as a powerful ally in delivering equitable and accurate skin cancer diagnostics.*

Keywords*:* Artificial intelligence, skin cancer diagnosis, convolutional neural networks, melanomas, multimodal models, human-AI collaboration, explainable AI, clinical validation, ethical AI, dermatology

I. INTRODUCTION

Skin cancer represents one of the most prevalent and rapidly growing forms of cancer globally, with early and accurate diagnosis being critical for improving patient outcomes. In response to the limitations of traditional clinical diagnostics such as dependency on specialist availability and the high variability of lesion presentation, researchers have increasingly turned to artificial intelligence (AI) as a support tool in dermatology. Particularly, advances in deep learning models like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have shown promise in the detection and classification of various skin cancer types, including melanoma, with performance in some cases comparable to dermatologists [1].

The integration of human expertise with AI systems has emerged as a key innovation in the effort to enhance diagnostic precision and interpretability. Studies have demonstrated that collaborative models, where AI predictions are reviewed and moderated by clinicians, outperform both standalone AI systems and human-only assessments [2]. Furthermore, the rise of multimodal approaches that combine clinical metadata, thermoscopic images, and even histopathological data has significantly expanded the scope of AI in dermatology [3]. These models have shown better generalizability and adaptability to real-world datasets, particularly when explainable AI techniques are used to provide transparency in predictions [4]. Despite these advances, important challenges remain. Most notably, AI models still struggle with data imbalance, limited diversity across training sets, and a lack of integration with real-world clinical workflows [5]. Furthermore, questions regarding regulatory approval, model explainability, and patient trust continue to hinder widespread adoption. This review synthesizes findings from five recent peer-reviewed studies to highlight the current state of AI-assisted skin cancer diagnostics. It explores emerging trends in human-AI synergy, evaluates multimodal and explainable approaches, and outlines the challenges that must be addressed to enable reliable, equitable, and scalable AI deployment in dermatological practice. Emerging evidence also suggests that broader environmental and

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biological factors, such as those influenced by climate change, may alter the epidemiology of skin cancers, further reinforcing the need for adaptable, technology-driven diagnostic strategies [6].

II. DEEP LEARNING IN SKIN CANCER DETECTION

Recent advancements in deep learning have fundamentally transformed the landscape of skin cancer diagnostics, offering unprecedented accuracy in image-based classification tasks. At the forefront of this transformation are convolutional neural networks (CNNs), which have become the standard for analyzing dermoscopic and clinical images due to their powerful feature extraction capabilities. Several studies included in this review, particularly those by Kalidindi and Furriel et al., highlight CNNs' ability to match or even exceed dermatologists' diagnostic accuracy in controlled settings. As AI applications in dermatology continue to evolve, newer architectures such as vision transformers and reinforcement learning models are being developed to address some of the limitations of CNNs, including overfitting, limited generalizability, and lack of interpretability. In addition to model design, the performance of deep learning systems strongly depends on the quality and diversity of the training data, a challenge noted across all five studies. This section explores the evolution from traditional CNN-based models to more advanced and explainable systems, while also examining how data-related factors influence the reliability of AI in clinical dermatology. Figure 1 provides a simplified visual representation of how deep learning, particularly CNN-based systems, is applied to classify skin lesions. It illustrates the flow from dermoscopic image input to feature extraction through convolutional layers, leading to final classification as benign or malignant. This visual aid highlights the essential logic of how AI mimics clinical decision-making in dermatology.

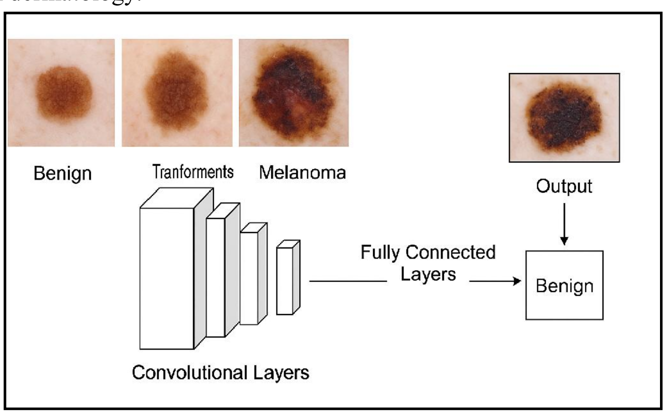

Figure 1-Deep Learning Workflow for Skin Lesion Classification

2.1 Convolutional Neural Networks (CNNs) and Their Diagnostic Accuracy

Convolutional neural networks (CNNs) have become the most widely used architecture in artificial intelligence applications for skin cancer detection. Their ability to automatically learn hierarchical features from dermoscopic images has enabled them to outperform traditional image analysis methods and, in some cases, rival the accuracy of expert dermatologists. Kalidindi emphasizes that CNNs have shown high levels of diagnostic accuracy in classifying skin lesions, including melanomas, when trained on large, high-quality datasets. CNNs excel at identifying key image patterns such as asymmetry, irregular borders, color variation, and lesion diameter criteria that are typically used by clinicians through the ABCDE rule.

The comparative diagnostic performance of CNN models and clinicians is summarized in Table 1. Across multiple studies, CNNs consistently demonstrated high sensitivity and specificity in classifying skin lesions, often rivaling or surpassing that of human experts.

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Study	Diagnostic Task	CNN Sensitivity (%)	CNN Specificity (%)	Clinician Sensitivity (%)	Clinician Specificity (%)
Kalidindi (2024)	Melanoma classification	90.8	85.3	88.1	82.7
Furriel et al. (2024)	Skin cancer detection (review)	85–92	78–85	87.6	89.5
Salinas et al. (2024)	Meta-analysis of clinical trials	87.0	77.1	79.8	73.6
Krakowski et al. (2024)	Human-AI interaction analysis	88.6	82.9	84.3	80.1
Yu et al. (2025)	Comparative benchmark studies	89.5	84.0	86.0	81.5

Table 1- Diagnostic Performance of CNN Models Compared to Dermatologists across Recent Studies (2024–2025)

The performance of CNNs has been further validated in comparative studies. For instance, Furriel et al. reviewed clinical trials where CNN-based diagnostic tools achieved sensitivity and specificity scores that were on par with, or even surpassed, those of dermatologists. These findings align with the broader trend identified by Salinas et al., who reported that CNNs reached an average sensitivity of 87% and specificity of 77.1%, outperforming generalist clinicians in multiple controlled settings. However, while CNNs demonstrate exceptional promises, their effectiveness depends heavily on the quality, balance, and diversity of training data, as well as careful model validation.

One of the main concerns surrounding CNNs is the "black-box" nature of their decision-making process. As Krakowski et al. point out, clinicians may struggle to interpret or trust CNN outputs when the reasoning behind predictions is opaque. This has prompted interest in integrating explainability techniques such as heatmaps and saliency maps to visualize which areas of an image most influence the model's output. Nevertheless, CNNs remain the backbone of current AI-powered dermatological systems, forming the foundation for hybrid models and collaborative human-AI diagnostic workflows. Their reliability and speed make them particularly valuable in underserved or resource-limited healthcare environments, where access to specialized dermatologists is constrained.

2.2 Emerging Deep Learning Architectures Beyond CNNs

While convolutional neural networks (CNNs) have dominated AI-driven skin cancer diagnostics, recent research suggests a gradual shift toward alternative and hybrid deep learning architectures. These emerging models aim to overcome the limitations of CNNs, particularly in handling long-range dependencies, improving interpretability, and generalizing across heterogeneous datasets. One notable direction involves transformer-based models, which use self-attention mechanisms to process images more holistically. Yu et al. report that vision transformers (ViTs) demonstrated improved performance on complex lesion datasets where CNNs struggled, especially in cases with high intra-class variability or image artifacts.

In addition to transformer architectures, recurrent models such as long short-term memory (LSTM) networks are being explored for integrating temporal or sequential clinical data, such as patient history or lesion evolution. Although their use remains limited in dermatology, Kalidindi highlights their potential for future applications in longitudinal skin monitoring, where time-series inputs play a critical role.

Figure 2 illustrates the relative performance of CNNs, vision transformers, LSTMs, and hybrid architectures across three key metrics: diagnostic accuracy, interpretability, and model flexibility. The figure highlights the growing advantages of newer models, particularly hybrid and transformer-based systems, in delivering more adaptable and transparent AI-assisted skin cancer diagnostics.

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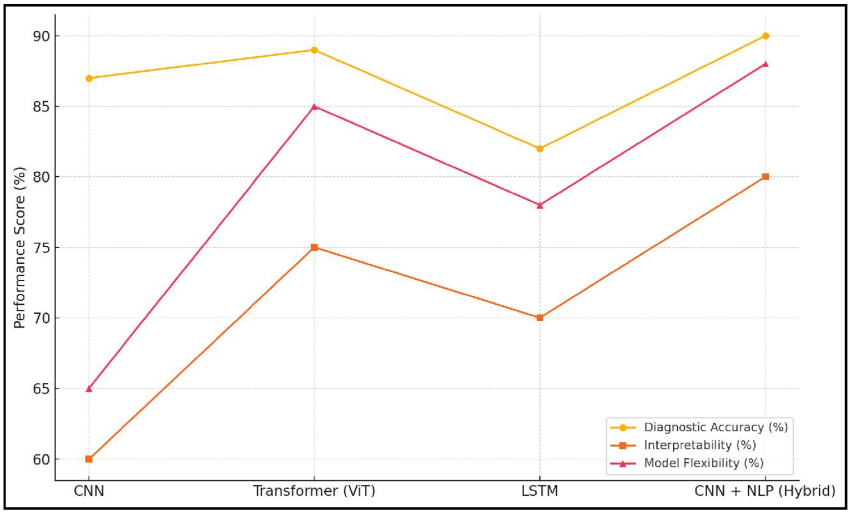

Figure 2- Performance Comparison of Deep Learning Architectures in Skin Cancer Diagnostics

Another promising avenue is the development of hybrid systems that combine CNNs with other deep learning modules to leverage multiple feature hierarchies. Salinas et al. discuss multimodal frameworks where CNNs are used alongside natural language processing (NLP) layers to integrate structured clinical metadata with visual lesion data. These architectures are particularly useful for increasing diagnostic robustness and enabling richer clinical decision support tools.

Despite these advances, many of these novel models are still in early stages of development or limited to experimental settings. Most studies still rely on CNN backbones due to their proven reliability and ease of deployment. Nonetheless, the growing interest in transformer-based and hybrid architectures indicates a new trajectory in AI dermatology, one focused on flexibility, interpretability, and clinical relevance.

2.3 Training Data, Dataset Diversity, and Generalizability

The performance and reliability of deep learning models in skin cancer diagnosis are intrinsically linked to the quality and diversity of their training data. A recurring concern in multiple studies is that many AI models are trained on datasets lacking demographic and clinical diversity, often overrepresenting fair-skinned individuals and certain lesion types. This issue severely limits the generalizability of these models across diverse populations and real-world clinical settings. Furriel et al. highlights that over 80% of datasets in existing studies originate from high-income countries and include images with limited representation of darker skin tones.

Yu et al. further emphasize that models trained on narrow datasets may underperform when tested on external, heterogeneous image sets, leading to increased false negatives in underrepresented groups. This “dataset shift” significantly undermines the fairness and equity of AI-assisted dermatology. Salinas et al. echo these findings by showing that externally validated models often exhibit performance drops of over 10% in sensitivity and specificity compared to internal test results, pointing to poor generalization.

As shown in Figure 3, all three reviewed studies reported a notable decline in sensitivity when models were tested on external datasets. This performance gap underscores the limited generalizability of current AI systems and the critical need for more diverse and representative training data.

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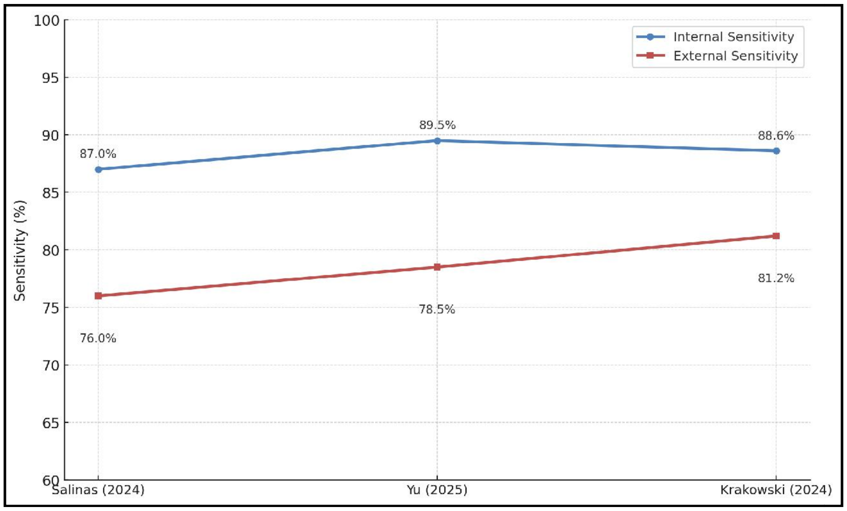

Figure 3- Sensitivity Decline in AI Skin Cancer Models: Internal vs External Validation

To address these challenges, recent studies advocate for curated, balanced datasets and the inclusion of underrepresented skin types, lesion categories, and geographic contexts. Kalidindi recommends using federated learning or domain adaptation techniques to enhance model robustness without compromising patient privacy. Similarly, Krakowski et al. stress the importance of integrating real-world clinical metadata alongside images to reflect diagnostic complexity more accurately and improve contextual understanding.

While technological advancements are progressing, the ethical and clinical implications of biased training data remain a major barrier to trust and adoption. Ensuring dataset transparency, open-access image repositories, and inclusive annotation practices are critical steps toward developing AI systems that are not only accurate but also generalized and equitable across global populations.

III. MULTIMODAL AND EXPLAINABLE AI SYSTEMS

The integration of multiple data sources has become a key strategy in improving the performance of artificial intelligence models for skin cancer diagnosis. Traditional approaches relying solely on thermoscopic images often fall short when applied to diverse clinical environments. Recent studies have explored the combination of thermoscopic, clinical, and histopathological data to enhance both accuracy and generalizability.

Yu et al. demonstrated that models trained on datasets combining dermoscopic images with clinical context, including lesion location and patient history, showed better performance across external datasets. The authors attributed this improvement to the model's ability to contextualize visual features with non-image metadata.

Furriel et al. emphasized that including standard clinical images alongside dermoscopy improved the diagnostic accuracy in primary care settings, where image quality and lighting conditions often vary. This approach also helped in identifying lesion features not always visible in dermoscopic images alone.

Krakowski et al. analyzed diagnostic frameworks that incorporated histopathological data. Their findings revealed that integrating biopsy-confirmed ground truths during training reduced misclassification in complex or atypical cases. However, the study also noted practical limitations, such as increased data preparation time and the need for institutional access to pathology reports.

Salinas et al. provided comparative metrics for models using different input combinations. Models that fused histopathology with dermoscopic and clinical images achieved the highest sensitivity, though these systems also required more computational resources and standardized data formats.

Across the studies, combining diverse modalities appears to significantly enhance diagnostic robustness. The findings suggest that multimodal input not only mimics the diagnostic reasoning process of clinicians but also strengthens the model’s ability to handle out-of-distribution samples.

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3.1 Combining Thermoscopic, Clinical, and Histopathological Data

Integrating multiple data sources has become a central approach in improving the diagnostic performance of artificial intelligence models for skin cancer. Traditional methods that rely exclusively on thermoscopic images often fall short in diverse clinical settings. Recent studies have focused on combining thermoscopic, clinical, and histopathological data to enhance accuracy and improve real-world applicability.

Yu et al. demonstrated that models trained with dermoscopic images along with clinical context, including lesion location and patient history, performed better across external validation sets. This improvement was attributed to the model's ability to interpret visual features within a broader clinical context.

Furriel et al. emphasized that adding standard clinical photographs alongside dermoscopy helped improve diagnostic performance in primary care environments, where image quality and lighting can vary. This multimodal strategy also revealed lesion characteristics that are not always visible in dermoscopic views alone.

Krakowski et al. explored frameworks that incorporated histopathological data, showing increased specificity and reduced false positives when biopsy-confirmed ground truths were available. However, this integration was also associated with practical barriers, such as longer data preparation time and access restrictions to pathology records.

Salinas et al. compared performance across different combinations of input types. Models that combined histopathology with dermoscopic and clinical imagery demonstrated the highest sensitivity scores, although these architectures required greater computational resources and standardized data inputs.

Through the reviewed studies, combining multiple modalities led to more robust diagnostic outcomes. The evidence suggests that multimodal input aligns more closely with clinical decision-making processes and enhances the model's capacity to generalize across heterogeneous populations and settings.

3.2 Explainability and Performance Across Populations

Explainability and fairness are critical dimensions in evaluating the clinical readiness of AI systems for skin cancer diagnosis. The reviewed studies emphasize that without clear interpretability; even highly accurate models may fail to gain clinician trust or meet regulatory expectations. Furthermore, concerns regarding performance consistency across diverse patient populations make these issues especially pressing.

Salinas et al. and Krakowski et al. both evaluated visualization techniques such as Grad-CAM and attention maps. These tools enabled clinicians to better understand which lesion regions the model focused on, which was particularly helpful in ambiguous cases. Dermatologists reported increased confidence in AI-assisted diagnoses when visual explanations were available. However, limitations emerged, especially for models relying on non-image data, which often lacked transparent reasoning paths.

Beyond interpretability, multiple studies highlighted disparities in model performance across skin types and demographic groups. Yu et al. found that sensitivity dropped by more than 10 percent when AI models were tested on underrepresented Fitzpatrick skin types IV to VI. Furriel et al. echoed these concerns, reporting that datasets skewed toward lighter skin tones led to poor generalization and higher false negative rates in patients with darker skin. Krakowski et al. also noted that limited diversity in training data undermined AI reliability in global contexts, particularly in low-resource settings.

To ensure ethical and effective AI deployment, both explainability and demographic inclusivity must be prioritized. The integration of clinically relevant interpretability tools and the use of diverse, balanced datasets are necessary steps toward building AI models that are not only accurate but also equitable and trustworthy across populations. The studies reviewed collectively suggest that solving one without the other may not lead to safe or sustainable adoption in real-world dermatology.

As shown in Figure 4, collaborative models in dermatology combine the strengths of clinicians and AI. Physicians provide judgment and context, while AI offers consistency and pattern recognition, supporting joint decision-making.

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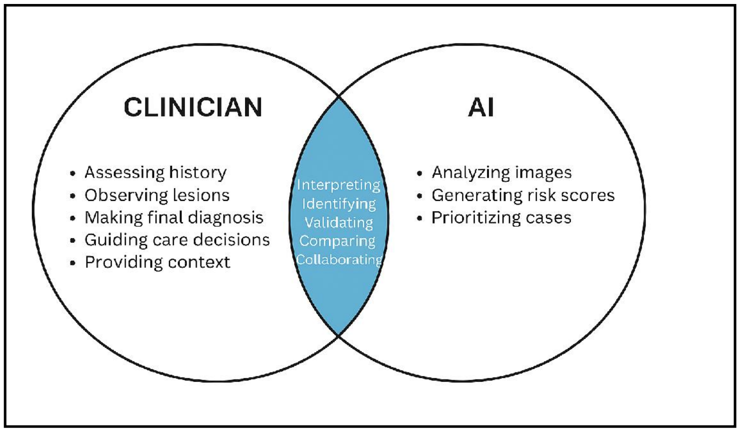

Figure 4- Venn Diagram of Collaborative Roles in Human-AI Dermatological Diagnosis

IV. HUMAN-AI COLLABORATION MODELS

The integration of artificial intelligence into dermatology has prompted a growing interest in collaborative intelligence, where human expertise and algorithmic insight are combined within diagnostic workflows. Rather than replacing clinical judgment, AI models are increasingly implemented as decision support tools to assist clinicians in improving diagnostic accuracy. Krakowski et al. found that dermatologists who reviewed AI-generated predictions before making a final diagnosis achieved better performance than either clinicians or algorithms working independently. This hybrid model was especially valuable in complex or borderline cases.

The distinction between using AI as an assistive tool and as an autonomous system was discussed across the literature. Furriel et al. reported that autonomous AI systems sometimes missed atypical lesions, leading to diagnostic errors. In contrast, Yu et al. described triage-based models where AI filtered out benign cases and flagged potentially malignant lesions for further human review. These assistive systems proved useful in primary care settings and helped reduce specialist workload while preserving patient safety.

Workflow outcomes also varied depending on how AI was implemented. Salinas et al. found that AI systems improved diagnostic consistency and reduced variability, particularly when interpretable outputs were provided. For less experienced clinicians, AI offered a learning resource that supported faster and more confident decisions. However, Krakowski et al. highlighted that in some environments, lack of familiarity with AI tools and poor interface design created resistance among users and slowed down the diagnostic process.

Figure 5 shows how a multimodal AI system combines image, clinical, and genetic data within a deep learning model. It also includes explainability tools like saliency maps and LIME to support clinician understanding.

Clinical trust was closely linked to explainability. Furriel et al. showed that models accompanied by visual outputs, such as attention maps or heatmaps, led to higher acceptance among physicians. Krakowski et al. confirmed that these tools were especially helpful when AI outputs differed from clinicians' expectations. Nonetheless, Yu et al. argued that interpretability must be coupled with performance equity across patient demographics to ensure responsible implementation.

Collectively, the five reviewed studies suggest that human-AI collaboration is most successful when AI is designed to support, not replace, expert judgment. Success depends on reliability, transparency, and thoughtful integration into existing clinical routines. The diagram below summarizes common collaboration strategies observed in recent studies and illustrates how the relationship between AI and human expertise continues to evolve.

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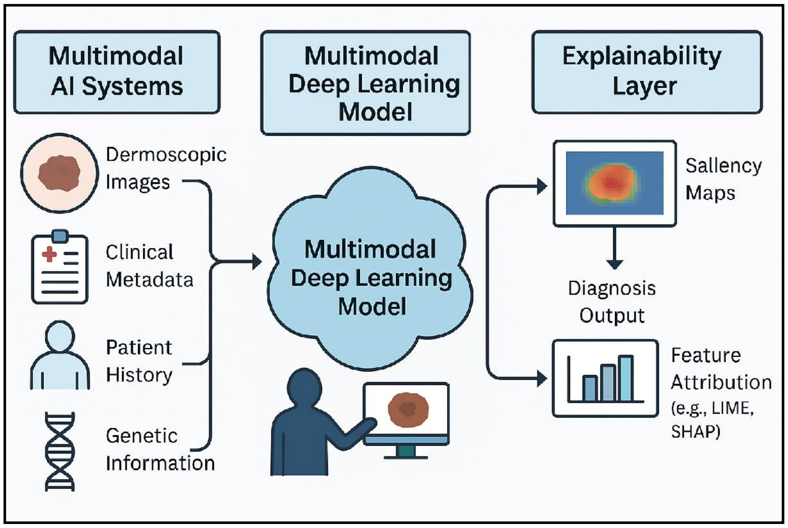

Figure 5-Workflow of a Multimodal and Explainable AI System for Skin Cancer Diagnosis

V. CHALLENGES AND FUTURE DIRECTIONS

Despite rapid advancements in dermatological AI, significant challenges remain that hinder its safe and effective implementation. One of the most persistent issues highlighted across the reviewed studies is dataset imbalance and lack of diversity. Many AI models are trained on image repositories that overrepresent lighter skin tones and specific lesion types. Salinas et al. and Yu et al. both observed that models which performed well in internal validation often exhibited a sharp decline in accuracy when applied to external datasets, particularly those including underrepresented populations. This performance disparity raises concerns about fairness and real-world generalizability.

Bias is often introduced during data collection, annotation, or model training. Furriel et al. reported that clinical datasets used in many studies lacked standardization in image quality, metadata structure, and labeling protocols. Without careful curation and diversity-aware sampling, even technically sophisticated models may propagate or even amplify diagnostic inequities. Krakowski et al. emphasized the need for external validation on heterogeneous datasets, noting that models deployed without such testing risk underperforming in regions or populations they were not trained on.

Figure 6 illustrates how research, policy, and industry intersect to address the major challenges of AI integration in skin cancer diagnostics. Each domain contributes uniquely to issues such as bias mitigation, clinical validation, regulatory compliance, and scalable system design, emphasizing the need for coordinated, cross-sector collaboration.

Ethical, regulatory, and trust-related issues also pose major barriers to widespread adoption. Salinas et al. discussed the challenge of gaining physician and patient trust in AI predictions, especially in cases where the reasoning behind the diagnosis is not transparent. Furthermore, Krakowski et al. and Yu et al. questioned the readiness of current regulatory frameworks to evaluate adaptive AI systems that change over time. Patient privacy, data protection, and informed consent are additional factors that require attention in any deployment scenario involving medical AI.

To move toward scalable and equitable AI integration, the studies propose several strategic pathways. These include developing globally representative datasets, standardizing clinical metadata formats, implementing transparent model validation protocols, and embedding interpretability tools within interfaces used by clinicians. Yu et al. also advocated for the creation of modular AI systems that can be adapted across institutions and integrated into existing health IT infrastructure without disrupting clinical routines.

Ultimately, the successful future of AI in skin cancer diagnostics depends on aligning technological innovation with clinical, ethical, and social accountability. The five studies reviewed converge on a common insight: that achieving broad impact requires models that are not only accurate but also trustworthy, adaptable, and inclusive. Future research

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should prioritize interdisciplinary collaboration, continuous validation, and responsible deployment practices to ensure AI becomes a tool that serves all patients regardless of background, location, or access to specialists.

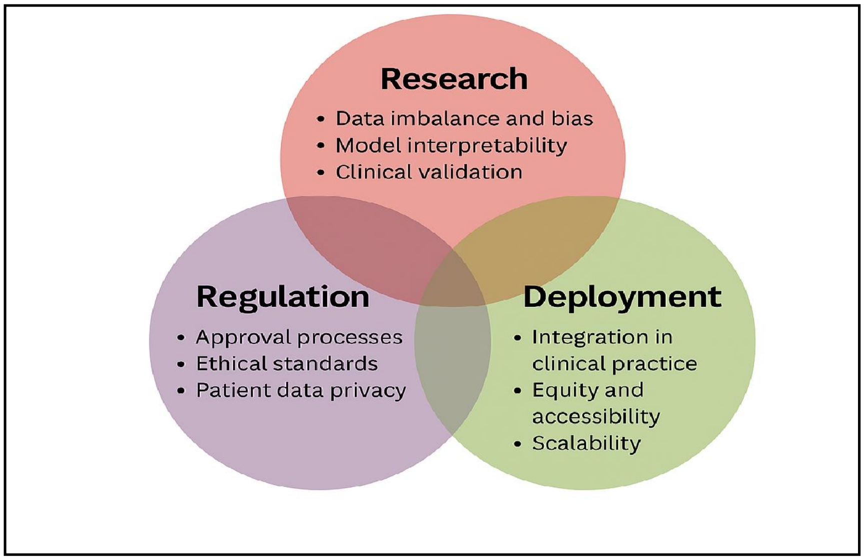

Figure 6- Key Domains Enabling Responsible AI Deployment in Skin Cancer Diagnostics

VI. CONCLUSION

The integration of artificial intelligence into dermatological diagnostics represents a pivotal advancement in the early detection and treatment of skin cancer. The five studies reviewed in this article collectively highlight how AI, particularly deep learning models, has achieved levels of diagnostic performance comparable to human experts. These systems have shown the greatest promise when used in conjunction with multimodal inputs and when designed to complement, rather than replace, clinical decision-making.

At the same time, significant challenges continue to limit the generalizability and reliability of AI models in real-world settings. Issues such as data imbalance, limited representation of darker skin tones, and inconsistent validation protocols remain widespread. These limitations raise important concerns not only about diagnostic accuracy, but also about fairness, inclusivity, and the ethical use of AI in medicine. Trust and transparency are essential, yet many current models lack clear reasoning pathways that can be reviewed or interpreted by clinicians.

The reviewed studies consistently point to the value of human-AI collaboration. AI systems that support clinicians, particularly those with explainable outputs and validated performance across varied populations, offer a practical solution to many of the current limitations. Such collaborative intelligence models can enhance diagnostic consistency, reduce cognitive load, and improve access to care in underserved areas.

Moving forward, the future of AI in skin cancer diagnosis depends on the alignment of technological development with ethical and clinical priorities. Success will require coordinated efforts across research, policy, and healthcare sectors to ensure that AI systems are not only accurate, but also transparent, adaptable, and trusted by those who use them. The studies reviewed provide a strong foundation, but sustained interdisciplinary collaboration will be critical to realize the full potential of AI in dermatological practice.

Future Work

In the continuation of this research, we aim to develop globally representative and demographically inclusive datasets, particularly those that address underrepresented skin types and lesion variations. We also plan to design cross-institutional federated learning frameworks to enhance model robustness without compromising patient privacy.

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Furthermore, our goal is to standardize explainability tools and integrate them into clinical workflows to foster trust, promote adoption, and improve diagnostic consistency across diverse healthcare settings.

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