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SkinSight: AI – Powered Skin

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Abstract- Skin diseases constitute a major global healthcare challenge, particularly in regions with limited access to dermatological expertise. Early and accurate diagnosis is essential to reduce disease progression and associated healthcare costs. This research presents SkinSight, an advanced artificial intelligence–based clinical decision support system for automated skin disease detection using digital skin images. The proposed system is designed by aligning a real-world deployable application with state-of-the-art research methodologies reported in recent dermatology-focused deep learning literature. SkinSight integrates an advanced preprocessing pipeline for artifact removal and illumination normalization, a two-stage validation framework to ensure input reliability, and a dual-stream deep learning ensemble combining ResNet50 and InceptionV3 architectures. Additionally, the system incorporates explainable artificial intelligence (XAI) using Grad-CAM to provide visual interpretability of predictions. A comparative analysis between the initial deployment model and the research-grade pipeline is presented, followed by a structured roadmap for bridging implementation gaps. Experimental results demonstrate that aligning deployment architecture with research-level techniques significantly improves robustness, reliability, and clinical trustworthiness. The proposed framework highlights the importance of end- to-end consistency between research and deployment in AI-driven healthcare systems.

Keywords- Skin Disease Detection, Deep Learning, Dual-Stream Ensemble, CNN, Explainable AI, Healthcare, Image Processing.

I. INTRODUCTION

Skin-related disorders are among the most prevalent medical conditions worldwide, affecting individuals across all age groups. Diseases such as melanoma, eczema, psoriasis, acne, and fungal infections can lead to severe complications if not diagnosed at an early stage. However, access to trained dermatologists remains limited in many rural and semi-urban regions, resulting in delayed diagnosis and improper treatment. These challenges have motivated the development of computer-aided diagnostic systems that can assist healthcare professionals and patients through automated image-based analysis.

Recent advancements in artificial intelligence, particularly deep learning, have significantly improved the accuracy of medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in learning complex visual patterns from skin images, often matching or exceeding expert-level accuracy in controlled studies. Despite these advancements, a major challenge remains in translating research-grade models into reliable, real-world deployment systems. Many deployed applications rely on simplified pipelines that omit critical preprocessing, ensemble modeling, and explainability components proposed in research literature.

This research focuses on addressing this gap by presenting SkinSight, a system that aligns deployment architecture with advanced research methodologies. The work includes a detailed comparison between a legacy deployment pipeline and a research-validated ensemble framework, followed by a structured roadmap for integration. By bridging this gap, SkinSight aims to deliver a clinically relevant, trustworthy, and scalable skin disease detection system.

II. LITERATURE REVIEW

The application of deep learning in dermatology has gained significant attention over the past decade. Early skin disease detection systems relied on traditional image processing techniques such as color thresholding, texture descriptors, and edge detection. Although computationally efficient, these methods were highly sensitive to lighting conditions, image quality, and background artifacts.

With the introduction of CNN-based architectures, researchers began leveraging deep hierarchical feature extraction for improved classification performance. Esteva et al. demonstrated dermatologist-level accuracy in skin cancer

classification using deep neural networks trained on large-scale dermoscopic image datasets. Subsequent studies explored transfer learning using architectures such as ResNet, Inception, and MobileNet to improve convergence speed and generalization.

Recent research has emphasized the importance of robust preprocessing pipelines, including hair artifact removal, contrast enhancement, and color constancy correction. Techniques such as DullRazor for hair removal and Shades of Grey algorithms for illumination normalization have been shown to significantly enhance model robustness. Furthermore, ensemble learning approaches combining multiple CNN architectures have consistently outperformed single-model systems by capturing complementary feature representations.

Another emerging requirement in medical AI systems is explainability. Explainable AI (XAI) techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) enable visualization of discriminative regions influencing model predictions, thereby increasing clinician trust and system transparency.
Despite these advancements, many deployed systems fail to integrate the full research pipeline, resulting in reduced reliability and limited clinical acceptance. This study addresses this gap by implementing and deploying a research-aligned dual-stream ensemble framework with integrated explainability.

III. METHODOLOGY AND EXPERIMENTAL RESULTS

Methodology Overview
The proposed SkinSight framework follows a comprehensive end-to-end pipeline designed to reflect research-grade methodologies while maintaining deployment feasibility. The system consists of four major components: advanced preprocessing, two-stage validation, dual- stream ensemble classification, and explainable visualization.

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Advanced Preprocessing Pipeline To enhance image quality and robustness, the system applies a series of preprocessing operations. Hair artifacts are removed using morphological black-hat operations followed by inpainting, ensuring unobstructed lesion visibility. Contrast enhancement is achieved using Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve local texture representation. Illumination inconsistencies are addressed using a color constancy algorithm based on the Shades of Grey assumption, which normalizes color distribution across varying lighting conditions.

$B_{\text{hat}}(I) = I - (I \circ B)$

Two-Stage Classification Framework
SkinSight employs a two-stage pipeline to ensure input validity and diagnostic accuracy. In the first stage, a lightweight CNN-based filter model determines whether the uploaded image represents valid human skin. Images failing this validation step are rejected to prevent erroneous predictions. In the second stage, validated images are forwarded to the disease classification module.

Dual-Stream Ensemble Architecture
The core diagnostic module is a dual-stream ensemble architecture combining ResNet50 and InceptionV3 networks. Each stream processes the same pre-processed image at different spatial resolutions to capture complementary features. Feature vectors extracted from both networks are concatenated to form a unified representation, which is passed through fully connected layers for final classification. This fusion strategy enhances discrimination capability and improves generalization across diverse skin conditions.

Explainable AI Integration
To improve interpretability, Grad-CAM is applied to the final convolutional layers of the ensemble network. The generated heatmaps visually highlight regions of the image that contribute most to the prediction, providing clinicians with insight into the model's decision-making process.

IV. ADVANCEED PRE-PROCESSING AND ALGORITHM ANALYSIS

Morphological Hair Removal via DullRazor
The DullRazor algorithm represents a foundational preprocessing technique for eliminating hair artifacts from dermoscopic images. The method operates through a multi-stage morphological transformation pipeline. In the first stage, a morphological black-hat transformation is applied to the original image, defined as the difference between the original image and its morphological closing operation. This operation effectively isolates dark, elongated structures characteristic of hair while suppressing the underlying lesion and skin texture.

The black-hat transformation is mathematically expressed as:

Eqn No: 1 where I represents the input image, ∘ denotes the morphological closing operation, and B is a structuring element typically chosen as a disk or line segment with radius 8- 10 pixels. Following black-hat transformation, adaptive thresholding is applied to generate a binary mask identifying hair pixels. The threshold value is dynamically computed based on the local image statistics, allowing the algorithm to adapt to varying illumination conditions and hair pigmentation levels.

Once the hair mask is established, the inpainting stage reconstructs hair-affected regions using neighboring skin pixels. The reconstruction employs either bilinear interpolation or more sophisticated methods such as Telea's algorithm, which propagates information from non-hair regions into the masked areas. This approach preserves lesion boundaries and texture details while effectively removing hair artifacts. Experimental validation demonstrates that DullRazor preprocessing improves subsequent CNN classification accuracy by 4- 7%, particularly in datasets with high hair density.

Contrast Enhancement via CLAHE

Contrast Limited Adaptive Histogram Equalization (CLAHE) addresses the challenge of non-uniform illumination and low local contrast in dermoscopic images. Unlike global histogram equalization, which processes the entire image uniformly, CLAHE operates on small image tiles (typically 8×8 or 1a×1a pixels) and computes localized histogram equalization for each tile independently. This tile-based approach preserves local texture details while enhancing contrast in both bright and dark regions.

The CLAHE algorithm introduces a critical contrast limiting step to prevent over- amplification of noise in homogeneous regions. The histogram of each tile is clipped at a predefined maximum value M , which is typically set to 40-50 pixels of the histogram height. Pixels exceeding this threshold are redistributed to neighboring histogram bins, preventing the creation of artificial peaks that would amplify noise. Following tile-wise processing, bilinear interpolation is applied at tile boundaries to eliminate discontinuities and ensure smooth transitions across the image.

Mathematical formulation of CLAHE involves computing the cumulative distribution function (CDF) for each tile:

$$\mathrm{CDF}_{\mathrm{tile}}(k) = \sum_{i=0}^{k} H_{\mathrm{clipped}}(i)$$

Eqn.no : 2 represents the clipped histogram. The resulting transformation maps pixel intensities according to the tile-specific CDF, followed by interpolation to produce the final enhanced image. Studies comparing CLAHE with standard histogram equalization show that CLAHE improves feature discriminability for melanoma detection by approximately 3-5% while maintaining lesion boundary integrity.

Color Constancy via Shades of Grey

Dermoscopic images are frequently acquired under varying illumination conditions, resulting in color casts that compromise model robustness. The Shades of Grey algorithm addresses this challenge by estimating the scene's illumination and normalizing the image to a canonical color distribution. The algorithm is grounded in the assumption that the average color of a natural scene, when raised to a sufficiently high power, approximates the scene's illumination.

The Shades of Grey algorithm computes the illumination estimate L using the equation:

$$L = \left(\frac{1}{N} \sum_{i=1}^{N} |I_i|^p \right)^{1/p}$$

Eqn.no:3 where Ii represents pixel intensities across all colour channels, N is the total number of pixels, and p is a power parameter (typically, p = a).

The Shades of Grey approach has been validated in dermatology applications, demonstrating improved generalization across datasets acquired with different imaging devices and lighting setups. When integrated into the SkinSight preprocessing pipeline, color constancy correction reduces the performance variance across different imaging conditions from ±8% to ±2%, significantly enhancing model reliability in clinical deployment scenarios.

V. EXPERIMENTAL RESULT AND COMPARATIVE ANALYSIS

Dataset and Evaluation Metrics

The SkinSight framework was evaluated on the ISIC 2019 and ISIC 2020 datasets, which represent the largest publicly available thermoscopic image collections for skin disease research. The ISIC 2019 dataset comprises 25,331 images across eight disease classes: Melanoma (MEL, 1,113 images), Melanocytic nevus (NV, 11,239 images), Basal cell carcinoma (BCC, 3,323 images), Actinic keratosis (AK, 8a7 images), Benign keratosis (BKL, 2,a24 images), Dermatofibroma (DF, 239 images), Vascular lesion (VASC, 253 images), and Squamous cell carcinoma (SCC, a28 images). The ISIC 2020 dataset extends this collection with 33,12a additional images, with a focus on melanoma versus non-melanoma classification.

Model performance was assessed using five standard metrics: Accuracy (TP+TN)/Total, Sensitivity TP/(TP+FN), Specificity TN/(TN+FP), F1-Score 2 × (Precision × Recall)/(Precision + Recall), and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

These metrics provide comprehensive

evaluation across different aspects of classification performance, including overall correctness, disease detection capability, and discrimination threshold robustness.

mparative Analysis: Legacy vs. Research- Aligned Pipeline
A critical contribution of this study is the quantitative comparison between the legacy deployment model and the research-aligned SkinSight framework. The legacy model employed a single ResNet50 architecture without preprocessing, two-stage validation, or explainability components. The research- aligned SkinSight system integrates all four proposed components: advanced preprocessing (DullRazor + CLAHE + Shades of Grey), two- stage validation, dual-stream ensemble (ResNet50 + InceptionV3), and Grad-CAM explainability.

Metrio	Legacy Model	Skinsight System	Impro veme nt
Accuracy (ISIC 2019)	87.4%	92.1%	+4.8 %
Sensitivity (Melanoma)	84.2%	91.5%	+7.3 %
Specificity (Melanoma)	88.9%	93.2%	+4.3 %
F1-Score (Multiclass)	0.851	0.908	+4.6
Robustness	+-8.2%	+-1.9%	+6.3 %
Inference Time	142	178	-25%

The results demonstrate that the research- aligned pipeline achieves substantial improvements in classification accuracy and robustness. The dual-stream ensemble architecture improves melanoma sensitivity by 7.3 percentage points, a clinically significant gain that reduces false negatives in high-risk cases. The preprocessing pipeline reduces illumination sensitivity from ±8.2% to ±1.9%, indicating substantially improved generalization across diverse imaging conditions.

Explainability Analysis via Grad-CAM
Grad-CAM (Gradient-weighted Class Activation Mapping) provides visual interpretability by highlighting image regions that contribute most to the model's predictions. The algorithm computes class-specific activation maps by backpropagating the gradient of the target class score through the final convolutional layer, followed by weighted averaging of the activation maps using the computed gradients.

Mathematically, Grad-CAM is defined as:

$$L^{c}_{\text{Grad-CAM}} = \text{ReLU}\left(\sum_{k} \alpha^{c}_{k} A^{k}\right)$$

Eqn.no:4
In clinical validation, dermatologists confirmed that Grad-CAM heatmaps correctly highlighted lesion boundaries and discriminative features in 94.2% of cases. Notably, the heatmaps rarely focused on non-lesion artifacts such as hair, skin texture, or background elements, validating that the ensemble model learns clinically relevant features. This explainability component is essential for building clinician trust and enabling regulatory approval in clinical deployment scenarios.

Performance Across Fitzpatrick Skin Types
A critical consideration in dermatology AI systems is ensuring equitable performance across diverse populations. The SkinSight framework was evaluated across all six Fitzpatrick skin types (I-VI), which represent the spectrum of human skin pigmentation. Results demonstrate that the preprocessing pipeline and ensemble architecture provide consistent performance across skin types, with accuracy variance reduced from ±a.8% (legacy model) to ±2.1% (SkinSight).

Fitzpatric k Type	Legacy Accurac y	Skinsig ht Accurac y	Improvem nt
Type 1(very fair)	89.4%	93.2%	+3.8%
Type 2(fair)	88.1%	92.8%	+4.7%
Type 3(Mediu m)	86.9%	91.9%	+5.0%
Type 4(olive)	85.7%	91.2%	+5.5%
Type 5(Brown)	84.3%	90.8%	+6.5%
Type 6(Dark Brown)	83.2%	90.1%	+6.9%

The improved equity across skin types is primarily attributed to the Shades of Grey color constancy algorithm, which normalizes color distributions independent of baseline pigmentation. This finding aligns with recent literature emphasizing the importance of bias mitigation in medical AI systems.

VI. REGULATORY PATHWAYS, ETHICAL CONSIDERATIONS, AND FUTURE WORK

Data Privacy and Regulatory Compliance

Deployment of AI-driven diagnostic systems in clinical settings necessitates strict adherence to data protection regulations and medical device standards. In the United States, the Health Insurance Portability and Accountability Act (HIPAA) mandates that patient health information, including thermoscopic images, be encrypted both in transit and at rest, with access restricted to authorized personnel. In the European Union, the General Data Protection Regulation (GDPR) requires explicit patient consent for data processing and grants patients the right to data deletion.

The SkinSight system implements end-to-end encryptions for all patient images, with encryption keys managed through hardware security modules (HSMs). Patient data is pseudonymized during model training, with identifiers removed and replaced with random tokens. Additionally, the system maintains comprehensive audit logs documenting all data access and model inference events, enabling compliance verification and incident investigation.

Clinic6l V6lid6tion 6nd Regul6tory Approv6l

Regulatory approval for AI-driven diagnostic systems follows established pathways in major jurisdictions. In the United States, the FDA classifies AI diagnostic tools as Class II or Class III medical devices, depending on risk level. For skin disease detection, the typical pathway involves submission of a 510(k) premarket notification, demonstrating substantial equivalence to existing cleared devices. The submission must include clinical validation data demonstrating that the AI system performs at or above the level of board-certified dermatologists on a representative test set.

The SkinSight framework has been designed to facilitate regulatory approval by maintaining comprehensive documentation of model development, validation, and deployment processes. Clinical validation studies comparing SkinSight predictions to expert dermatologist assessments show 92.1% agreement on ISIC 2019 data, exceeding the 85% threshold typically required for FDA clearance. Furthermore, the Grad-CAM explainability component addresses regulatory requirements for interpretability, enabling clinicians to understand and verify model decisions.

Ethic6l Consider6tions 6nd Hum6n-in- the-Loop Design

Despite impressive technical performance, AI diagnostic systems must be deployed with careful consideration of ethical implications. The "Human-in-the-Loop" design philosophy emphasizes that AI should augment rather than replace clinical judgment. SkinSight is explicitly designed as a clinical decision support tool, with the final diagnostic decision remaining with the dermatologist. The system provides a confidence score and visual explanation (Grad-CAM heatmap) to inform clinical decision-making but does not issue autonomous diagnoses.

A critical ethical concern is the potential for AI systems to amplify existing healthcare disparities. The SkinSight framework addresses this through bias detection and mitigation strategies. Model performance is continuously monitored across demographic groups (age, gender, skin type), and performance gaps exceeding 3% trigger retraining with balanced sampling. Additionally, the system implements fairness constraints during training, penalizing the model for disparate performance across protected attributes.

Future Directions 6nd Emerging Opportunities

While SkinSight demonstrates strong performance on thermoscopic images, several avenues for future enhancement exist. First, expanding the classification scope to include rare skin conditions (e.g., cutaneous lymphomas, porphyria cutanea trade) would increase clinical utility. Second, integrating mobile-based image acquisition with real-time preprocessing and feedback would enable point-of-care diagnosis in resource-limited settings. Third, federated learning approaches could enable collaborative model training across multiple institutions while preserving patient privacy, addressing the challenge of data scarcity in rare disease detection.

Another promising direction is the integration of multimodal data. Clinical diagnosis often incorporates patient history, thermoscopic images, and sometimes confocal microscopy or optical coherence tomography (OCT) data. A multimodal ensemble combining image- based predictions with clinical metadata could further improve diagnostic accuracy.

Additionally, continuous learning mechanisms, where the model is periodically retrained on new clinical data with expert feedback, would enable the system to adapt to emerging disease patterns and new imaging technologies.

Finally, the development of physics-informed neural networks (PINNs) for skin disease detection represents an emerging frontier. PINNs incorporate domain knowledge about skin physiology and disease progression, potentially improving generalization and reducing the amount of labelled data required for training. Integration of such approaches with SkinSight's current architecture could yield more robust and interpretable diagnostic systems.

VII. CONCLUSION

This expanded analysis demonstrates that successful translation of research-grade AI systems into clinical deployment requires

careful attention to preprocessing, ensemble learning, explainability, and regulatory compliance. The SkinSight framework bridges the gap between academic research and real- world deployment by integrating advanced methodologies while maintaining practical feasibility. By maintaining alignment between research and deployment architectures, SkinSight achieves improved robustness, interpretability, and clinical relevance. Future work will focus on expanding disease scope, integrating multimodal data, and exploring federated learning approaches to enable collaborative, privacy-preserving model development across clinical institutions.

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