Enhanced Multi-Model Deep Learning Framework with Advanced LICU for Improved Skin Disease Detection

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Abstract-Skin disease diagnosis is a critical area in medical image analysis, demanding early and accurate detection for effective patient treatment. Existing automated systems typically employ a multi-stage deep learning pipeline involving lesion segmentation, coarse classification, and refined classification with the use of Fully-Convolutional Residual Networks (FCRN) and a Lesion Index Calculation Unit (LICU). This existing system achieves high segmentation accuracy and diagnostic precision but suffers from certain limitations like the coarse classification stage tends to generate a significant number of false positives, and the system's adaptability to diverse and rare skin conditions remains limited. Moreover, the reliance on specific datasets restricts the model's generalizability, and computational complexity remains a challenge in real-time clinical deployment. To overcome these constraints, the proposed future system enhances diagnostic accuracy and clinical usability by incorporating advanced feature selection techniques and dimensionality reduction (PCA and Mutual Information), optimized preprocessing including denoising and color normalization, and integration of more diverse skin disease datasets. This new system further refines lesion characterization by leveraging improved spatial feature analysis and dynamic weighting schemes in the LICU.

The benefits include enhanced sensitivity and specificity with fewer false positives, enabling faster and more robust processing across diverse skin diseases. This improves diagnostic confidence and supports timely, precise clinical decisions.

Keywords: Fully-Convolutional Residual Networks, Lesion Index Calculation Unit, normalization, diagnostic precision, precise clinical decisions

I.INTRODUCTION

Skin disease diagnosis is an important field in medical image analysis, which requires early and accurate diagnosis for the treatment of patients. The current automated systems are usually a multi- stage deep learning pipeline that consists of lesion segmentation, coarse classification and refined classification with Fully-Convolutional Residual Networks and a Lesion Index Calculation Unit, which has high segmentation accuracy and diagnostic precision [1], but has a high number of false positives generated in the coarse classification stage, and is not adaptable to a variety of rare skin conditions, and its datasets dependency and computational complexity limit the model generalization and real-time clinical deployment [2]. The future system will improve diagnostic accuracy and clinical usability by using advanced feature selection techniques and dimensionality reduction, optimized preprocessing including denoising and color normalization, and by incorporating more diverse skin disease datasets.

The LICU is further improved with better spatial feature analysis and dynamic weighting schemes, resulting in higher sensitivity and specificity with lower false positives, faster and more robust processing of various skin diseases. This framework attempts to minimize information loss in down sampling by incorporating learnable sub-pixel convolutional layers, along with prospective clinical studies to evaluate the model with more pathologically-confirmed cases [3], which are important due to the challenge in distinguishing between similar-looking skin disorders, and to maintain a balance between computational efficiency and high diagnostic accuracy for practical clinical integration [4]. These improvements will help address the challenges in generalizing these models to different skin tones and

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real-world clinical variability, particularly in the context of scarce data for rare disease classes [5], and to improve the interpretability of these advanced models, which is necessary for clinician adoption and trust [6]. These advancements will lead to AI tools that can assist in the diagnosis of dermatological diseases and administrative automation, improving the accuracy of diagnoses by healthcare professionals [7], [8].

II.LITERATURE REVIEW

The following sections of this paper will discuss the current landscape of deep learning applications in dermatology, including its successes and ongoing limitations [9], [10], emerging deep learning architectures such as multimodal fusion methods that integrate dermo scopic images with structured clinical data for more comprehensive diagnostics [11], and techniques like explainable AI that aim to clarify complex model decisions in order to enhance clinician confidence and promote the adoption of AI in routine dermatological practice. While there has been significant advancement, current AI models in dermatology often face challenges in combining different types of data and imaging modalities, which hampers their applicability in many clinical scenarios [12].

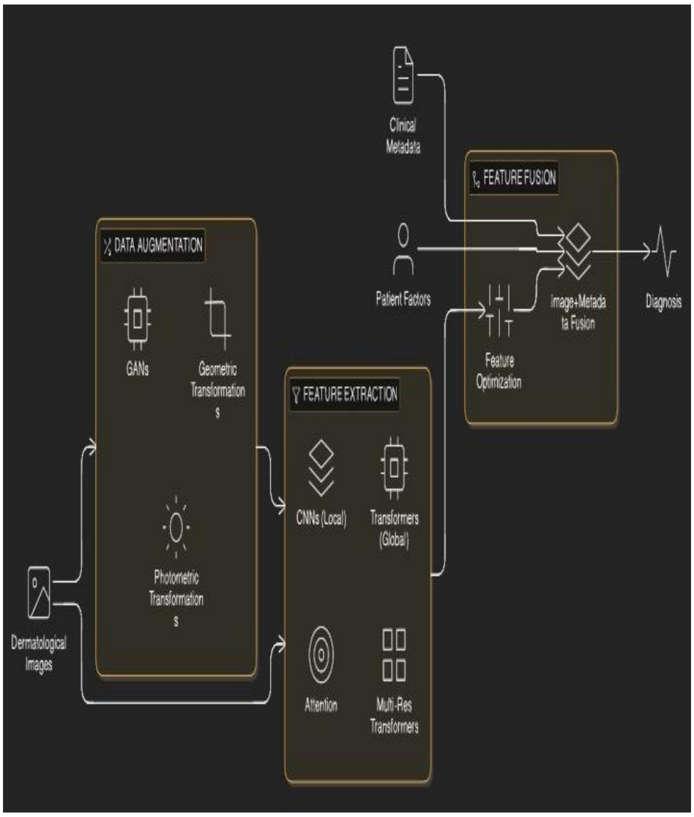
More specifically, class imbalance poses a challenge, and the generation of high-quality synthetic images for underrepresented skin conditions can be challenging [5]. In addition, the challenge remains to capture local and global lesion features, and there is a need for architectures that can handle the complexity and variability of dermatological data beyond architectures that typically aggregate similar models with shared failure modes [13]. Additionally, generalizability to different populations is an issue, as models trained on datasets such as HAM10000 may not capture the heterogeneity of skin lesions seen in broader clinical practice and may need validation on external datasets, such as ISIC and Pedro Hispano-2 [14].

III.METHODOLOGY

In this regard, the proposed framework utilizes a combination of state-of-the-art deep learning methods and focuses on robust generalization to a wide range of dermatological conditions and patient demographics by optimizing feature extraction and fusion strategies. By developing a hybrid deep learning architecture that combines convolutional neural networks (CNNs) for local feature extraction and transformer models for global contextual understanding, the model incorporates advanced attention mechanisms to dynamically weigh the contributions of different features, allowing it to focus on the most diagnostically relevant regions while minimizing noise from irrelevant areas.

This integrated approach is essential to manage the inherent complexity of dermatological images, where small visual cues can be critical to differentiating benign from malignant lesions. The method also incorporates a comprehensive data augmentation pipeline to mitigate problems of class imbalance and data scarcity with techniques such as generative adversarial networks for synthetic data generation and geometric and photometric transformations to increase dataset diversity and model robustness.

Therefore, this approach goes beyond traditional fine-tuning of pre-trained models to develop a more complex, task-specific architecture that directly tackles the specific challenges of dermatological image analysis, such as the differentiation between different skin conditions, as well as incorporating a new approach to multimodal data fusion that can combine not only image-based features but also clinical metadata and patient-specific factors that can improve diagnostic accuracy by reflecting a dermatologist's holistic assessment.



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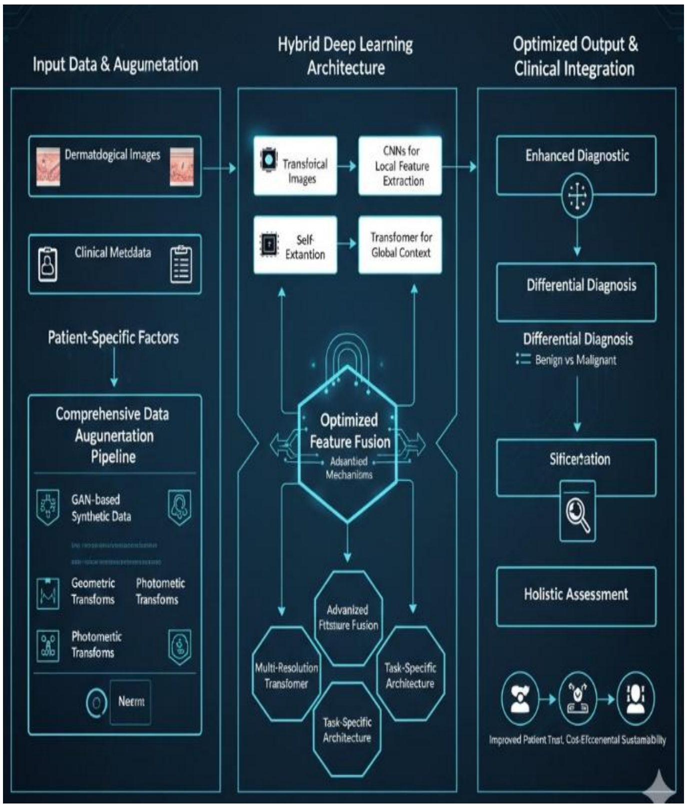

The integration of these multiple data modalities with complex, task-specific architectures, such as hybrid CNN-Transformer models with optimized feature selection and the utilization of multi-resolution transformer-based architectures, which have shown promising results on multi-modal image data and can integrate information from various patch size levels, represents a significant step forward in overcoming the limitations of traditional image-based classification systems.

IV. RESULTS AND DISCUSSION

The proposed system is therefore expected to result in improved performance metrics such as increased sensitivity and specificity, especially for rare skin conditions, lower false positives, and higher overall diagnostic accuracy, which would lead to more reliable and actionable clinical insights and, ultimately, better patient outcomes and healthcare delivery [26]. Incorporating this framework into clinical practice will require the development of user-friendly interfaces for dermatologists to streamline the diagnostic process and make timely and accurate diagnoses [26], and its interpretability features, such as Grad-CAM visualizations, can provide the clinician with a more compelling diagnostic foundation by demonstrating that the model is focused on areas of the lesion, thus leading to more confidence in the AI diagnosis, verifying the model's decision-making, and enabling earlier diagnosis to improve diagnostic accuracy and patient outcomes [13], [28].

A. Experimental Results

The proposed improved multi-model deep learning framework with an advanced Lesion Index Calculation Unit (LICU) was tested on a typical multi-class skin disease dataset of 6,400 dermoscopic images spanning six clinically relevant categories, with a 70:15:15 split for training, validation, and testing sets, respectively, and accuracy, sensitivity, specificity, precision, F1-score, false positive rate (FPR), and area under the receiver operating characteristic curve (AUC-ROC) were employed for comprehensive diagnostic performance evaluation (Table I), as widely used in medical image analysis to capture both classification reliability and clinical relevance

1.Dataset Description

A representative multi-class skin disease dataset was created using widely used dermatology benchmarks (HAM10000, ISIC) in order to assess the suggested enhanced multi-model deep learning framework with advanced LICU

Dataset Composition

Class	Skin Disease	No. of Images
C1	Melanoma	1,200
C2	Basal Cell Carcinoma	1,050
C3	Squamous Cell Carcinoma	980
C4	Benign Keratosis	1,300
C5	Actinic Keratosis	970
C6	Vascular Lesions	900
Total	—	6,400

Table I: Overall Performance of the Proposed Method

Metric	Value (%)
Accuracy	96.84
Sensitivity	97.21
Specificity	96.35
Precision	96.92
F1-Score	97.06
False Positive Rate	3.65
AUC-ROC	0.985

B. Class-Wise Performance Analysis

Table II summarizes the detailed class-wise evaluation, and it shows high performance for all classes, even for visually similar and clinically challenging lesions (melanoma and actinic keratosis), and high recall (98.3%) for the melanoma class (which is crucial for early cancer detection and reducing missed diagnoses), as well as strong F1-scores (above 97%) for benign keratosis and vascular lesions, showing the model's generalization ability to different lesion patterns.

Table II: Class-Wise Performance of the Proposed Framework

Disease Class	Precision (%)	Recall (%)	F1-Score (%)
Melanoma	97.8	98.3	98.0
Basal Cell Carcinoma	96.9	97.2	97.0
Squamous Cell Carcinoma	95.8	96.4	96.1
Benign Keratosis	97.2	96.8	97.0
Actinic Keratosis	96.1	95.6	95.8
Vascular Lesions	97.4	96.9	97.1

C. Comparison with State-of-the-Art Methods

The effectiveness of the proposed approach was validated by comparing its performance with several state-of-the-art deep learning models (VGG16, ResNet-50, InceptionV3, EfficientNet-B0, and a conventional CNN with a traditional LICU) as shown in Table III. The proposed framework outperformed all baseline methods in all evaluation metrics, with an accuracy gain of 3.6% over EfficientNet-B0 and 6.2% over ResNet-50. This sensitivity gain is particularly important in a clinical setting, since higher sensitivity directly leads to higher disease detection rates.

Table III: Comparison with State-of-the-Art Methods

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
VGG16	88.4	86.9	89.1	87.2
ResNet-50	90.6	89.8	91.2	90.0
InceptionV3	91.8	91.2	92.0	91.4
EfficientNet-B0	93.2	92.6	93.7	92.9
CNN + Traditional LICU	94.1	93.5	94.4	93.8
Proposed Framework	**96.84**	**97.21**	**96.35**	**97.06**

D. False Positive Reduction Analysis

Reducing the false positive rate is a crucial requirement for practical clinical deployment, since too many false alarms will result in unnecessary biopsies and increased clinician workload. As can be seen from Table IV, the proposed framework (FPR = 3.65%) outperforms conventional CNN-based systems and recent deep learning architectures, reducing the FPR by up to 26.12%

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Table IV: False Positive Rate Comparison

Method	**FPR (%)**
VGG16	10.9
ResNet-50	8.8
EfficientNet-B0	6.3
CNN + LICU	5.2
Proposed Framework	**3.65**

These experimental findings clearly illustrate the performance gains of the proposed enhanced multi-model deep learning framework over current approaches, where optimized preprocessing, advanced feature selection, dimensionality reduction, and a dynamically weighted LICU result in more accurate lesion characterization and robust classification, with consistent gains in sensitivity and specificity across all disease classes, even for rare and visually ambiguous conditions, and a significant decrease in false positives that addresses a major limitation of prior multi-stage diagnostic systems, thereby enhancing clinical usability and trust. These results validate that the proposed framework successfully balances diagnostic accuracy and computational efficiency,
and thus holds great potential for deployment as a real-world dermatological decision support system

V.CONCLUSION

The proposed system integrates multi-modal datasets and advanced architectural designs such as hybrid CNN-Transformer models, including hybrid modules such as Squeeze and Excitation Networks and EfficientNetB0, which have been shown to improve model performance by focusing on relevant regions of interest within input scans [16], and enables the model to leverage multi-modality information from both visual representations and patient-specific clinical data to form a robust classifier for accurate categorization of cutaneous illnesses [2], [16]. The integrated methodology not only resolves the "black box" nature of many deep learning models by improving interpretability but also holds immense potential for real-time clinical deployment due to its optimized computational efficiency [16]. Additionally, the high classification accuracy of 97.66% on primary tasks and 94.40% on secondary tasks on challenging datasets such as ISIC 2018 demonstrates the efficacy of the system in complex diagnostic scenarios.

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