Enhanced Multimodal Fusion Framework for Robust Skin Disease Classification – A Systematic Review

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Abstract: Skin diseases are among the most prevalent health conditions worldwide, requiring early and accurate diagnosis to prevent complications. Recent advancements in Artificial Intelligence, particularly Machine Learning, have enabled automated systems for skin disease classification using medical images. This paper presents a comprehensive approach to classifying skin diseases by leveraging convolution machine learning trained on dermoscopic and clinical image datasets. The proposed model improves the diagnostic accuracy by incorporating data augmentation and optimized feature extraction techniques. Experimental results demonstrate that the system achieves high accuracy and robustness across multiple skin disease categories. The study highlights the potential of AI-assisted diagnostic tools in Dermatology, especially in improving access to healthcare in resource-limited settings.

Keywords: Skin diseases, medical images, dermatology, Machine Learning

Introduction

Skin diseases are among the most prevalent health conditions worldwide, affecting millions of individuals and contributing significantly to the global healthcare burden. Early and accurate diagnosis is essential for effective treatment; however, access to specialized care in Dermatology remains limited in many low-resource and rural regions. This disparity highlights the urgent need for scalable and intelligent diagnostic solutions.

Recent advancements in Artificial Intelligence, particularly Machine Learning, have significantly improved the performance of automated skin disease classification systems. Modern deep learning models, including convolution neural networks and transformer-based architectures, have demonstrated strong capability in analyzing dermoscopic and clinical images. Recent studies show that AI systems are now being developed to classify a broad spectrum of skin diseases—not just skin cancer—indicating rapid progress in this field [1]. These advancements highlight the growing potential of AI to support dermatological diagnosis and improve healthcare accessibility.

Despite these developments, most existing approaches rely heavily on single mode data, particularly image-only inputs. In real clinical settings, diagnosis involves multiple factors such as patient demographics, medical history, and symptom descriptions. The absence of such contextual information limits model robustness and reduces clinical applicability. To address this limitation, recent research has emphasized the importance of multimodal frameworks that integrate heterogeneous data sources for improved diagnostic accuracy and decision-making.

Another critical challenge in skin disease classification is the issue of dataset bias and lack of diversity. Many datasets used for training AI models are skewed toward lighter skin tones, leading to reduced performance on underrepresented populations. A recent large-scale study demonstrated that AI-based diagnostic systems exhibit varying performance across different skin tones, underscoring the need for fairness-aware models and inclusive datasets [2]. Furthermore, research on skin color bias has shown that deep learning models can inherit and amplify disparities if not properly designed and evaluated [3].

In addition to bias, the generalization capability of current models remains limited. Systems trained on selected datasets often perform poorly in real-world environments due to variations in imaging conditions, device quality and population diversity. Recent work has highlighted that improving robustness and fairness is essential for the safe deployment of AI in clinical dermatology [4]. Emerging techniques such as fairness-aware learning and bias mitigation strategies have been proposed to address these challenges, including approaches that improve fairness without requiring sensitive demographic data [5].

To overcome these limitations, this study proposes an enhanced multimodal framework for skin disease classification that integrates image data, patient metadata and clinical textual information. By leveraging advanced deep learning architectures and cross-modal fusion strategies, the proposed system aims to improve diagnostic accuracy, robustness, and fairness across diverse populations. The framework is designed to better reflect real-world clinical practice and to support equitable healthcare delivery across global communities.

The key contributions of this work include the development of multimodal classification architecture, comprehensive evaluation across diverse datasets, and analysis of its effectiveness in reducing bias and improving generalization. Through this approach, the study aims to advance the field of AI-assisted dermatology and contribute toward more reliable and inclusive diagnostic systems.

Related work

The following Table 1 presents a comparative overview of existing skin disease classification techniques proposed by different researchers. The studies mainly focus on improving the accuracy, efficiency, and reliability of automated skin disease diagnosis using artificial intelligence and deep learning approaches. Various methods such as Convolutional Neural Networks (CNNs), transfer learning, Vision Transformers, ensemble learning, hybrid ML-DL models, and attention mechanisms have been employed for feature extraction and classification. The findings indicate that machine learning models generally achieve high classification accuracy and support early diagnosis of skin diseases. However, several limitations remain, including dataset imbalance, limited dataset diversity, high computational complexity, over fitting, scalability issues, and challenges in real-world clinical deployment.

Table 1: Existing Skin Disease Classification techniques

Author(s)	**Objective**	**Methods Used**	**Key Findings**	**Limitations**
[6]	Automated classification of multiple skin diseases	CNN trained on dermoscopic datasets (HAM10000)	High accuracy; CNN outperformed traditional ML (SVM, KNN)	Performance affected by imbalanced dataset

[7]	Improve early detection of skin cancer	Deep learning (CNN, GANs, transfer learning, ensemble models)	Improved early diagnosis; handles class imbalance better	Dataset limitations; still challenges in real-world deployment
[8]	Enhance feature extraction for accurate classification	CNN + multi-scale channel attention mechanism	Better feature extraction and improved classification accuracy	High computation; misclassification among similar lesions
[9]	Compare CNN architectures for classification	ResNet50, VGG16, EfficientNetB0, InceptionV3	CNNs effective across 8 disease classes; strong performance	Small dataset ,risk of over fitting
[10]	Develop efficient CAD system for early diagnosis	Lightweight CNN-based Computer-Aided Diagnosis (CAD)	Efficient and accurate early detection system	Trade-off between speed and accuracy
[11]	Multi-class classification of skin diseases	Transfer learning (ImageNet pretrained models)	Achieved ~93.2% accuracy with high ROC-AUC	Limited dataset diversity; lacks real-world validation
[12]	Automated classification of common skin diseases	CNN-based architecture	Enables early diagnosis and improved healthcare outcomes	Requires large datasets for robustness
[13]	To reduce diagnostic bias in skin disease classification across diverse skin tones	Hybrid CNN + Vision Transformer (DermNet)	Improved fairness and reduced bias in predictions across different skin tone groups	Moderate classification accuracy
[14]	Enhance automated skin disease classification with transformer models and explainable AI	Vision Transformers, Swin Transformers, DinoV2, GradCAM, and SHAP	DinoV2 achieved 94.48% accuracy	Transformer models require high computational resources
[15]	Classify seven skin diseases using transfer learning CNN models	VGG16, MobileNet, ResNet50, InceptionV3, DenseNet, and NASNet	MobileNet achieved highest accuracy of 94.1% among tested models	Small dataset and limited disease categories reduced scalability
[16]	Improve skin disease classification using fusion networks	DenseNet and ConvNeXt fusion model	Fusion architecture enhanced feature extraction and classification accuracy	Increased model complexity and training time

[17]	Detect multiple skin diseases using ResNet deep neural network	ResNet-based CNN trained on skin disease image dataset	Achieved very high training and testing accuracy for 10 disease classes	Dataset collected from internet sources may affect reliability and real-world applicability
[18]	Develop hybrid ML-DL model for automated skin disease classification	CNN feature extraction combined with SVM, Decision Tree, KNN, and LightGBM	CNN with SVM achieved best accuracy of 91.04%	Limited dataset diversity and over fitting concerns
[19]	Improve skin lesion classification accuracy using ensemble learning	Weighted majority voting ensemble deep learning with CNN architectures	Ensemble learning improved diagnostic accuracy and robustness in lesion classification	High computational complexity and dependency on large datasets

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