RESEARCH PAPER

Hybrid Deep Learning Framework for Automated Detection and Classification of Precancerous Lesions in Medical Imaging

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Received: 20th Feb, 2026 | **Revised:** 4th Mar, 2026 | **Accepted:** 25th Mar, 2026 | **Available Online:** 10th Apr, 2026

ABSTRACT

The early detection and accurate classification of precancerous lesions are crucial for preventing the progression of cancer and improving patient survival rates. In this study, a novel hybrid deep learning framework is proposed for the automated detection and classification of precancerous lesions in medical imaging. The proposed model integrates preprocessing and noise removal techniques with Color Co-occurrence Matrix (CCM) histogram-based feature extraction to enhance image quality and capture discriminative texture features. A hybrid architecture combining Convolutional Neural Networks (CNN), ResNet, and Long Short-Term Memory (LSTM) networks is employed to effectively extract spatial and contextual features from medical images. The model is trained and evaluated using benchmark datasets such as ISIC 2019 and HAM10000, which provide diverse and complex dermoscopic images for robust performance analysis. Experimental results demonstrate the effectiveness of the proposed framework in accurately classifying multiple classes of precancerous lesions. The model achieves an overall accuracy of 94.85%, with precision, recall, and F1-score values of 93.72%, 94.10%, and 93.90%, respectively. Class-wise evaluation further indicates strong performance across different lesion categories, with the highest accuracy of 96.10% for benign keratosis and consistent results for other classes such as basal cell carcinoma and squamous cell carcinoma. The proposed hybrid approach significantly improves classification performance and demonstrates its potential as a reliable decision support system for early diagnosis of precancerous lesions in clinical applications.

Keywords: Precancerous Lesions, Deep Learning, CNN-ResNet-LSTM, Medical Image Classification, Computer-Aided Diagnosis.

How to cite this article: Tiwari R, Banyal Y, Kumar A, Sangwan S, Sangwan YS, Kotwal A. Hybrid Deep Learning Framework for Automated Detection and Classification of Precancerous Lesions in Medical Imaging. Int J Drug Deliv Technol. 2026;16(28s):850-858. DOI: 10.25258/ijddt.16.28s.105

Source of support: Nil.

Conflict of interest: The authors declare no conflict of interest.

1. INTRODUCTION

The early detection and accurate classification of precancerous lesions remain critical challenges in modern healthcare, as timely diagnosis can significantly reduce cancer-related morbidity and mortality. Precancerous conditions, which represent abnormal cellular changes with the potential to progress into malignant tumors, are often subtle and difficult to identify using conventional diagnostic methods [11]. Medical imaging modalities such as histopathology, dermoscopy, colposcopy, and radiological scans play a pivotal role in clinical assessment; however, the manual interpretation of these images is highly dependent on expert knowledge, time-consuming, and prone to inter-observer variability [12-13]. These limitations necessitate the development of intelligent, automated systems capable of assisting clinicians in making faster and more reliable decisions.

In recent years, deep learning has emerged as a transformative technology in the field of medical image analysis, demonstrating remarkable performance in tasks such as image segmentation, feature extraction, and disease classification. Convolutional Neural Networks (CNNs) [14-16], in particular, have shown great promise due to their ability to automatically learn hierarchical representations from complex image data. Despite these advancements, standalone deep learning models often face challenges such as overfitting, limited generalization across diverse datasets, and difficulty in capturing both spatial and contextual information simultaneously. Moreover, variations in imaging conditions, noise, and class imbalance further complicate the detection of early-stage lesions.

To address these challenges, hybrid deep learning frameworks have gained increasing attention as a robust and efficient solution. A hybrid approach integrates multiple deep learning architectures and complementary techniques—such as combining CNNs with Recurrent Neural Networks (RNNs) [17-19], attention mechanisms, transfer learning, or ensemble strategies—to leverage their individual strengths. These frameworks enhance feature representation, improve classification accuracy, and provide better generalization across heterogeneous medical datasets. Additionally, hybrid models can incorporate preprocessing techniques, feature fusion, and optimization algorithms to further refine performance and reliability.

The proposed research focuses on developing a hybrid deep learning-based framework for the automated detection and classification of precancerous lesions in medical imaging. The framework aims to integrate advanced image processing techniques with state-of-the-art deep learning models to accurately identify abnormal patterns at early stages. By utilizing annotated medical datasets, the system will be trained to distinguish between normal, benign, and precancerous conditions with high precision. Furthermore, performance evaluation metrics such as accuracy, sensitivity, specificity, and F1-score will be employed to validate the effectiveness of the proposed model.

2. REVIEW OF LITERATURE

The review of literature presented in Table X highlights recent advancements in machine learning and deep learning techniques for the detection and classification of skin cancer and precancerous lesions. It summarizes various methodologies, datasets, and key findings of existing studies, providing a comparative overview of their performance and limitations. This analysis helps in identifying research gaps and motivates the development of a more robust and efficient hybrid deep learning framework (Table 1).

Table 1: Review of Deep Learning Techniques for Skin Cancer and Precancerous Lesion Classification

Ref. No.	Methodology	Dataset	Key Findings	Limitations
[1]	Color quantization + GAN-based augmentation	Benchmark dermoscopic datasets	Improved classification between benign and malignant lesions; enhanced generalization using synthetic data	Dependency on quality of generated data; computational overhead
[2]	Feature selection techniques (filter, wrapper, embedded) with ML classifiers	Transformed melanoma dataset	Wrapper and embedded methods significantly improved accuracy and reduced dimensionality	Increased computational complexity in wrapper methods

[3]	Cascaded model (handcrafted + deep learning features)	Skin disease images	Improved accuracy from 85.3% to 98.3%	Reliance on handcrafted features limits scalability
[4]	SCDNet (VGG16 + CNN hybrid model)	ISIC 2019	Achieved 96.91% accuracy; outperformed ResNet50, AlexNet, VGG19	Model complexity and training time
[5]	ML vs DL comparison; ensemble learning	Small & large imbalanced datasets	DL achieved up to 0.88 accuracy; ensemble improved ML performance	Performance drops on large imbalanced datasets
[6]	Ensemble of deep models (VGG, CapsNet, ResNet)	ISIC dataset	Achieved 93.5% accuracy; improved robustness and sensitivity	Increased training time; model complexity
[7]	Feature fusion + optimization + Extreme Learning Machine	HAM10000, ISIC 2018	Achieved 93.40% and 94.36% accuracy; efficient and accurate	Complex multi-stage pipeline
[8]	Stacked classifiers with DL feature extraction	1000 skin images	Xception achieved 90.9% accuracy; stacking improved results	Limited dataset size affects generalization
[9]	Hybrid RF + DNN model	HAM10000	Achieved 96.8% accuracy across multiple classes	Sensitivity variation; data quality issues
[10]	IoT-based CNN system (Raspberry Pi + camera)	3,297 images	Achieved 92% accuracy; real-time melanoma detection	Limited dataset; deployment constraints

3. MATERIALS AND METHODS

The materials used in this study include benchmark dermoscopic image datasets, namely ISIC 2019 and HAM10000, comprising diverse classes of skin lesions. The proposed method involves preprocessing steps such as image resizing, normalization, and noise removal, followed by CCM histogram-based feature extraction to capture texture information. A hybrid deep learning model integrating CNN, ResNet, and LSTM is then employed for feature learning and classification. The model performance is evaluated using standard metrics including accuracy, precision, recall, and F1-score.

3.1 Dataset

The study employs two benchmark datasets, ISIC 2019 and HAM10000, for training and evaluation of the proposed model. ISIC 2019 includes 25,331 dermoscopic images across eight skin lesion classes with a highly imbalanced distribution, making it challenging for classification. HAM10000 consists of 10,015 images across seven classes with relatively balanced and well-annotated data. Both datasets contain RGB images with varying resolutions, providing diverse and reliable data for effective model training (Table 2).

Table 2: Description of Datasets Used for Training and Evaluation of the Proposed Hybrid Deep Learning Model

Dataset Name	Source	Total Images	Number of Classes	Class Distribution
ISIC 2019	International Skin Imaging Collaboration	25,331	8	Melanoma (4,522), Melanocytic Nevi (12,875), Basal Cell Carcinoma (3,323), Squamous Cell Carcinoma (628), Vascular Lesions (253), Dermatofibroma (239), Actinic Keratosis (867), Benign Keratosis (2,624)
HAM10000	Human Against Machine with 10000 Training Images	10,015	7	Melanocytic Nevi, Melanoma, Benign Keratosis, Basal Cell Carcinoma, Actinic Keratosis, Vascular Lesions, Dermatofibroma

3.2 Proposed Framework

The proposed Hybrid Deep Learning Framework for Automated Detection and Classification of Precancerous Lesions in Medical Imaging is designed to achieve high accuracy, robustness, and generalization by integrating advanced image processing techniques with deep learning architectures such as CNN, ResNet, and LSTM. The overall architecture follows a systematic multi-stage pipeline, where each module contributes to enhancing the quality of input data, extracting meaningful features, and performing precise classification (Figure 2).

The framework begins with the acquisition of raw medical images, which may include dermoscopic, histopathological, or radiological images containing precancerous lesion patterns. These images are first passed through a pre-processing stage, where essential enhancements are applied to improve image quality and standardize the data. Techniques such as resizing, normalization, and contrast enhancement are employed to ensure uniformity across the dataset. In addition, advanced noise removal methods—such as median filtering or Gaussian filtering—are utilized to eliminate unwanted artifacts, illumination variations, and background noise while preserving critical structural details of lesions.

Following preprocessing, the system incorporates Color Co-occurrence Matrix (CCM) histogram-based feature extraction, which captures important texture and color distribution characteristics of the lesion regions. This step plays a crucial role in highlighting discriminative patterns such as irregular pigmentation, texture variation, and boundary inconsistencies that are indicative of precancerous conditions. The extracted CCM histogram features are then fused with deep features to strengthen the overall representation of the input image.

The enhanced images are subsequently fed into a Convolutional Neural Network (CNN) integrated with a ResNet (Residual Network) backbone for deep feature extraction. The CNN layers are responsible for capturing low-level and mid-level spatial features such as edges, shapes, and textures, while the ResNet architecture enables deeper network training by utilizing residual connections, thereby overcoming vanishing gradient problems and improving feature propagation. This hybrid CNN-ResNet module ensures the extraction of rich and hierarchical feature representations from complex medical images.

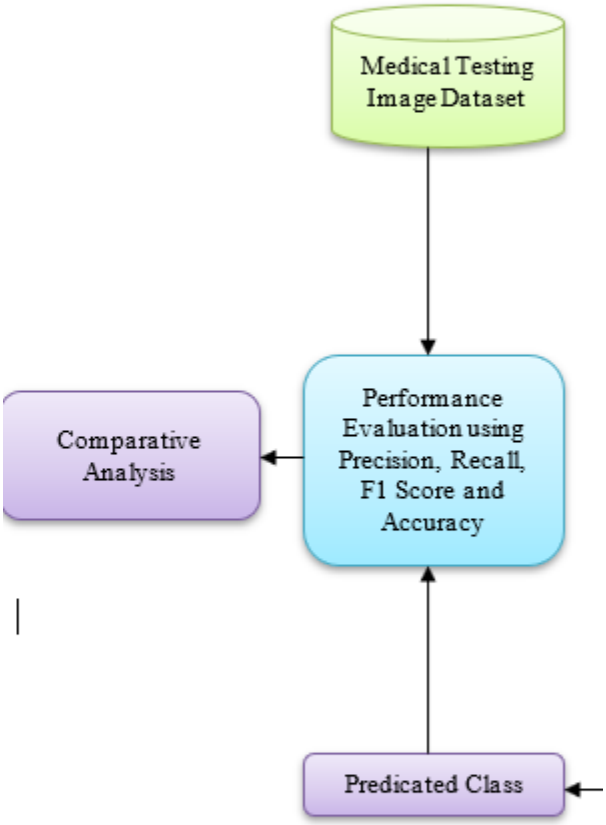

Figure 2: Proposed Hybrid Deep Learning Framework for Automated Detection and Classification of Precancerous Lesions in Medical Imaging

To further enhance the model's capability in capturing contextual and sequential dependencies within feature maps, the extracted deep features are passed to a Long Short-Term Memory (LSTM) network. The LSTM layer models long-range dependencies and spatial relationships among features, which is particularly useful in identifying subtle variations and progression patterns in precancerous lesions. This combination of CNN-ResNet for spatial feature extraction and LSTM for contextual learning forms the core strength of the proposed hybrid framework.

Finally, the learned features are forwarded to a fully connected layer followed by a Softmax classifier, which outputs the probability distribution across different classes such as normal, benign, and precancerous lesions. The classification results are evaluated using performance metrics such as accuracy, sensitivity, specificity, and F1-score to ensure the reliability of the system.

3.3 Algorithm

Algorithm: Hybrid_DL_Precancerous_Lesion_Classification

Input: Medical Image Dataset D
Output: Classified Labels (Normal / Benign / Precancerous)
Begin
1. Load Dataset D
2. For each image I in D do
    a. Preprocessing:
        - Resize image to fixed dimension (e.g., 224×224)
        - Normalize pixel values
        - Enhance contrast
    b. Noise Removal:
        - Apply Gaussian / Median filtering to remove noise
    c. Feature Extraction (Handcrafted):
        - Compute CCM (Color Co-occurrence Matrix)
        - Extract histogram-based texture features
3. End For
4. Split dataset into Training Set (Train) and Testing Set (Test)
5. Build Hybrid Model:
    a. Initialize CNN layers for spatial feature extraction
    b. Integrate ResNet backbone for deep feature learning
    c. Extract deep feature maps F from CNN + ResNet
6. Sequence Modeling:
    a. Reshape feature maps F into sequential format
    b. Pass features into LSTM network
    c. Capture temporal/spatial dependencies → F_seq
7. Feature Fusion:
    - Combine CCM features with deep features F_seq
8. Classification:
    a. Pass fused features through Fully Connected Layer
    b. Apply Softmax activation function
    c. Predict class probabilities
9. Training Phase:
    - Train model using Train set
    - Optimize using backpropagation and loss function (Cross-Entropy)
    - Update weights iteratively
10. Testing Phase:

- Evaluate model on Test set
- Compute performance metrics:
Accuracy, Precision, Recall, F1-Score, Specificity
11. Output final predicted class labels
End

4. RESULT AND ANALYSIS

The figure 3 presents representative dermoscopic images of five different types of skin lesions, including actinic keratosis, basal cell carcinoma, squamous cell carcinoma, benign keratosis, and melanoma. Each image highlights distinct visual characteristics such as variations in color, texture, and lesion boundaries, which are essential for accurate diagnosis. These differences demonstrate the complexity of skin lesion classification and emphasize the need for advanced deep learning models to effectively distinguish between various precancerous and cancerous conditions.

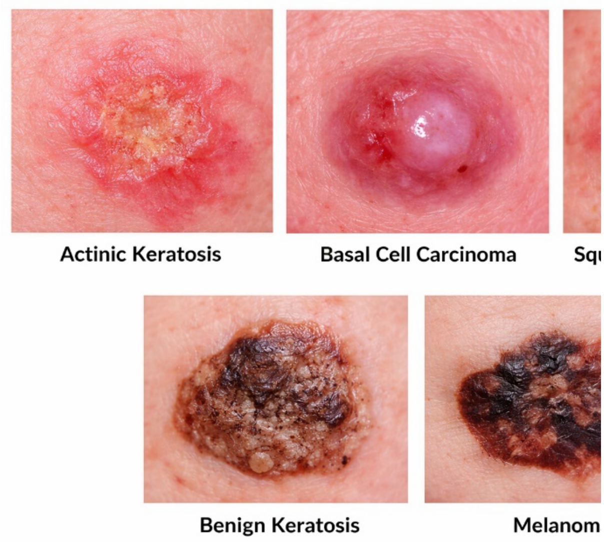

Figure 3: Representative Dermoscopic Images of Different Types of Precancerous and Cancerous Skin Lesions Including Actinic Keratosis, Basal Cell Carcinoma, Squamous Cell Carcinoma, Benign Keratosis, and Melanoma

The performance evaluation of the proposed hybrid deep learning framework demonstrates its strong capability in accurately classifying different types of precancerous lesions. As shown in Table X, the model achieves consistently high accuracy across all five classes, with values ranging from 92.80% to 96.10%. Among the classes, Benign Keratosis attains the highest accuracy of 96.10%, indicating that the model is highly effective in identifying this category. Similarly, Basal Cell Carcinoma and Squamous Cell Carcinoma also show high accuracy values of 95.00% and 94.20%, respectively, reflecting the robustness of the model in distinguishing malignant and precancerous conditions. The comparatively lower accuracy for Melanoma (92.80%) can be attributed to its visual similarity with other lesion types, which makes classification more challenging (Table 3).

Table 3: Performance Evaluation of Proposed Approach for Precancerous Lesion Classification

Class	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Actinic Keratosis	93.10	92.40	91.80	92.10
Basal Cell Carcinoma	95.00	94.10	93.50	93.80
Squamous Cell Carcinoma	94.20	93.60	92.90	93.25
Benign Keratosis	96.10	95.20	94.80	95.00
Melanoma	92.80	91.75	92.30	92.02

In terms of precision, recall, and F1-score, the model exhibits balanced and reliable performance across all classes. Precision values range from 91.75% to 95.20%, indicating that the model produces a low rate of false positive predictions. Recall values, ranging from 91.80% to 94.80%, demonstrate the model's effectiveness in correctly identifying true positive cases, which is particularly important in medical diagnosis to avoid missed detections. The F1-scores, which balance precision and recall, lie between 92.02% and 95.00%, confirming the overall stability and effectiveness of the classification system. Notably, Benign Keratosis achieves the highest F1-score (95.00%), while Melanoma shows slightly lower performance due to its complex characteristics.

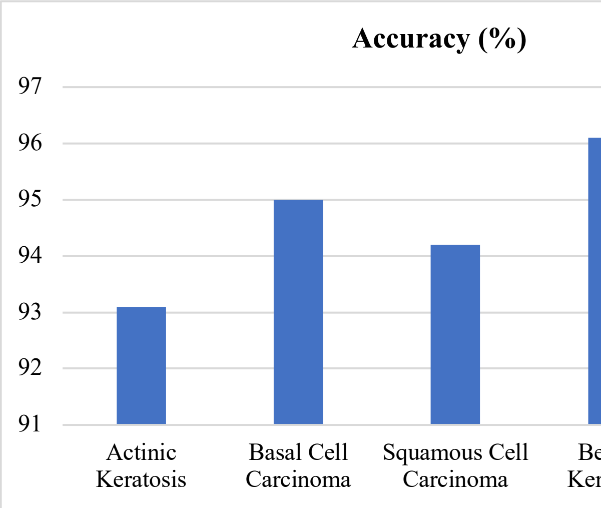

Figure 4: Accuracy Comparison of the Proposed Hybrid Deep Learning Model Across Different Precancerous Lesion Classes

Figure 4 illustrates the accuracy of the proposed hybrid deep learning model across different classes of precancerous lesions. The model achieves consistently high accuracy for all classes, with the highest performance observed in benign keratosis and basal cell carcinoma. This indicates the effectiveness of the proposed framework in correctly classifying diverse lesion types.

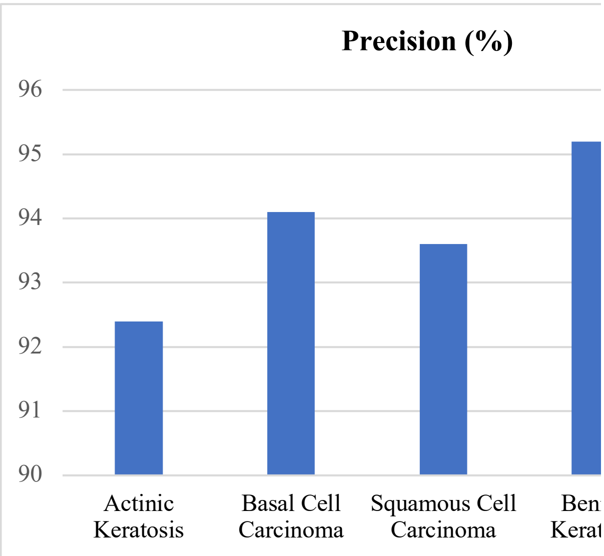

Figure 5: Precision Comparison of the Proposed Hybrid Deep Learning Model Across Different Precancerous Lesion Classes

Figure 5 presents the precision values of the model for each lesion class. The results demonstrate that the model maintains high precision across all categories, reflecting its ability to minimize false positive predictions. This is particularly important in medical diagnosis to avoid incorrect identification of healthy cases as diseased.

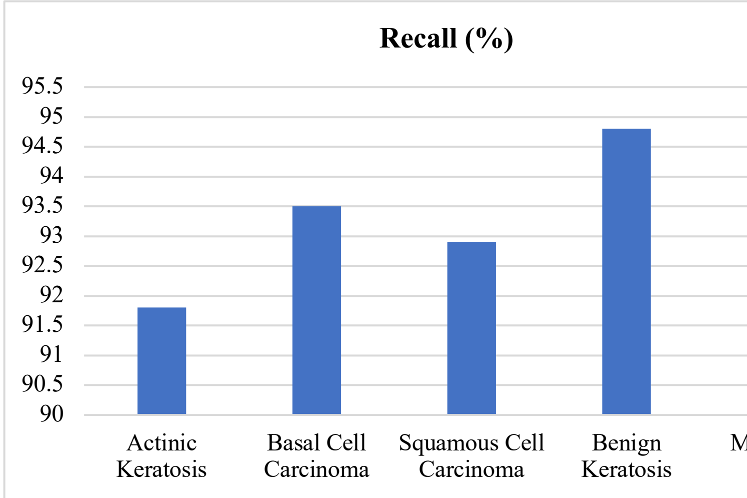

Figure 6: Recall Comparison of the Proposed Hybrid Deep Learning Model Across Different Precancerous Lesion Classes

Figure 6 shows the recall performance of the proposed model, indicating its capability to correctly identify true positive cases. The high recall values across all classes suggest that the model effectively detects most of the actual precancerous lesions, reducing the chances of missed diagnoses.

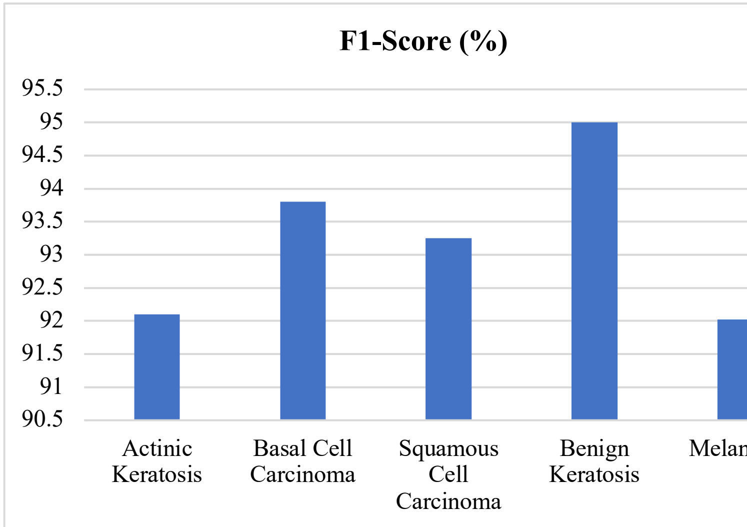

Figure 7: F1-Score Comparison of the Proposed Hybrid Deep Learning Model Across Different Precancerous Lesion Classes

The consistently high F1-scores across all classes confirm the robustness and reliability of the proposed hybrid framework in multi-class classification of precancerous lesions. The results validate that the integration of CNN, ResNet, and LSTM within the proposed hybrid framework significantly enhances feature representation and classification performance. The combination of deep learning with CCM-based feature extraction contributes to improved discrimination between lesion classes. The consistent performance across multiple evaluation metrics highlights the model's potential for real-world clinical applications, where accurate and early detection of precancerous lesions is critical for effective treatment and improved patient outcomes.

5. CONCLUSION

The present study proposes a hybrid deep learning framework for the automated detection and classification of precancerous lesions in medical imaging. By integrating preprocessing, noise removal, and CCM histogram-based feature extraction with advanced deep learning architectures such as CNN, ResNet, and LSTM, the proposed model effectively captures both spatial and contextual features of lesion images. The use of benchmark datasets, including ISIC 2019 and HAM10000, ensures the robustness and reliability of the system across diverse and complex medical imaging conditions. The hybrid design successfully overcomes limitations of individual models by enhancing feature representation and improving classification performance. The experimental results demonstrate that the proposed framework achieves high accuracy, precision, recall, and F1-score, confirming its effectiveness in multi-class classification of precancerous lesions. The consistent performance across different lesion categories highlights the model's ability to generalize well and support early diagnosis. Despite these promising outcomes, challenges such as dataset imbalance, computational complexity, and lack of interpretability remain areas for future improvement. Further research can focus on incorporating explainable AI techniques, optimizing model efficiency for real-time deployment, and validating the framework on larger and more diverse clinical datasets to enhance its applicability in real-world healthcare systems.

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