Jurnal Mandiri IT
Vol. 15 No. 1, July (2026), pp. 43-50

ISSN 2301-8984 (Print), 2809-1884 (Online)
Published by Institute of Computer Science

Attention-enhanced hybrid deep learning for skin cancer diagnosis with hierarchical feature fusion

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ARTICLE INFO

Article history:

Received Jun 300, 2026
Revised Jul 5, 2026
Accepted Jul 14, 2026

Keywords:

Deep Learning;
Hierarchical Feature Fusion;
Hybrid Attention Mechanism;
Image Classification;
Skin Cancer Diagnosis.

ABSTRACT

Skin cancer is one of the most prevalent cancers worldwide, making early and accurate diagnosis essential for improving patient outcomes and reducing mortality. However, automated skin lesion classification remains challenging due to high inter-class similarity, class imbalance, and variations in lesion appearance. This study proposes an attention-enhanced hybrid deep learning for skin cancer diagnosis with hierarchical feature fusion. The proposed framework integrates channel and spatial attention with hierarchical feature fusion to enhance discriminative feature learning and improve classification robustness. Experiments were conducted on the PAD-UFES-20 dataset using image preprocessing and data augmentation. The proposed model achieved approximately 98% training accuracy, 95% validation accuracy, and a validation loss below 0.5, outperforming DRMv2Net, DenseNet201, ResNet101, and MobileNetV2 while demonstrating faster convergence and stronger generalization. These findings demonstrate the potential of hybrid attention and hierarchical feature fusion to improve the reliability and robustness of artificial intelligence-based diagnostic systems in dermatology, supporting more effective clinical decision-making and early skin cancer screening.

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1. INTRODUCTION

Skin cancer is one of the most prevalent forms of cancer worldwide and represents a significant public health challenge due to its increasing incidence and potential mortality when diagnosis is delayed. Early detection plays a critical role in improving treatment outcomes and patient survival rates; however, accurate diagnosis remains challenging because skin lesions often exhibit substantial variations in color, texture, size, and shape, while different lesion categories may share highly similar visual characteristics. In recent years, deep learning techniques have emerged as powerful tools for automated skin cancer diagnosis, offering the ability to learn complex patterns directly from dermoscopic images (Aljohani et al., 2026; Bhargavi & Balakrishna, 2026; Liu et al., 2026). Their adoption has the potential to support dermatologists by improving diagnostic consistency, reducing workload, and enabling large scale screening programs.

Despite the remarkable progress achieved by recent deep learning models for skin cancer diagnosis (Alghamdi, 2026; Nguyen, 2025; Rezaei et al., 2025), several important challenges remain unresolved. Existing attention based architectures generally improve feature discrimination by emphasizing informative lesion regions; however, most employ either channel attention or spatial attention independently, limiting their capability to simultaneously capture inter-channel dependencies and spatial contextual information. Furthermore, conventional feature fusion methods typically combine only the final-layer representations, overlooking complementary information available in intermediate feature layers. Hierarchical feature fusion was therefore adopted to integrate multi-level features, enabling richer representations that preserve fine-grained textures together with high-level semantic information. Such limitations reduce the model's ability to accurately distinguish skin lesions with highly similar visual characteristics while maintaining computational efficiency. To address these limitations, this study proposes an Attention-Enhanced Hybrid Deep Learning for Skin Cancer Diagnosis with Hierarchical Feature Fusion. Unlike previous studies that simply integrate multiple pretrained networks or apply a single attention mechanism, the proposed architecture combines channel attention and spatial attention within a unified framework and subsequently performs hierarchical feature fusion across multiple feature extraction stages.

Beyond addressing existing performance limitations, the proposed architecture contributes to the development of intelligent skin cancer diagnosis systems by introducing a unified feature representation framework that jointly exploits hybrid attention and hierarchical feature fusion. Scientifically, the integration of channel and spatial attention enables the network to simultaneously model feature importance across channels and lesion regions, leading to more discriminative feature representations than conventional single-attention approaches. Furthermore, hierarchical feature fusion facilitates the interaction of low-level texture information with high-level semantic features, allowing the network to preserve fine-grained lesion characteristics while capturing global contextual information. This integrated learning strategy provides a more comprehensive representation of dermoscopic images, improving the model's capability to distinguish visually similar lesion categories and enhancing its generalization across diverse skin lesion patterns. Consequently, the conceptual contribution of this study is a unified deep learning framework that jointly integrates hybrid attention and hierarchical feature fusion, providing a more effective strategy for learning discriminative skin lesion representations than existing attention-only or conventional feature fusion approaches.

2. RESEARCH METHOD

A wide range of approaches has been explored, including feature fusion frameworks, lightweight attention based networks, hybrid architectures that combine convolutional neural networks and transformers, segmentation oriented models, and multimodal learning strategies (Table 1). These methods have achieved substantial improvements in classification accuracy, robustness, and computational efficiency when evaluated on widely used datasets such as PAD-UFES and HAM10000. However, the heterogeneous nature of these datasets, characterized by class imbalance, high intra-class variability, and strong visual similarity between different lesion categories, continues to challenge model training and generalization. To address these challenges, the proposed model combines hybrid attention mechanisms with a multi stage feature fusion strategy, aiming to enhance feature representation, improve classification balance and accuracy, and support greater adaptability in real world clinical settings.

Table 2. Relevant related work

References	Proposed Model	Metrics	Contributions	Limitations / Gap
(Rocha et al., 2025)	EOSA-Net: overlapping patch self-attention with convolution.	Acc 94.7%, AUC 98.4%	Achieved strong diagnostic performance while maintaining computational efficiency suitable for real-time applications.	Performance remains vulnerable to class imbalance and has not been extensively validated in clinical settings.
(Wen et al., 2022)	Ensemble of VGG-19, CapsNet, ViT with ML classifiers.	Acc 91.6%	Enhanced detection capability through ensemble learning, outperforming individual network architectures.	Effectiveness depends heavily on feature quality and has been evaluated only on binary classification tasks.
(Dash et al., 2023)	MFO-Fuzzy U-Net for lesion segmentation.	Acc 99.13%, F1 97.49%	Delivered highly accurate lesion segmentation with potential applicability in IoT enabled healthcare environments.	Requires substantial computational resources and has been tested on datasets with limited diversity.
(Nagdiya et al., 2025)	CNN, GoogleNet, ResNet with mean/median sampling.	Best CNN – Acc 73%, AUC 0.86	Improved dataset balance and model robustness through sampling-based strategies.	Susceptible to segmentation inaccuracies and exhibits limited effectiveness in

References	Proposed Model	Metrics	Contributions	Limitations / Gap
				multiclass classification scenarios.
(Cataldo et al., 2024)	DRMv2Net: fusion of DenseNet201, ResNet101, and MobileNetV2 with preprocessing and FC layers.	ISIC – Acc 96.11%; PAD-UFES – Acc 96.17%	Demonstrated superior detection performance by integrating feature fusion and preprocessing techniques.	Relies on large-scale datasets, incurs high computational costs, and lacks comprehensive external validation.
(Thanga Purni & Vedhapriyavad hana, 2024)	CNN with GAN-based augmentation and transfer learning.	Acc 86.1%, AUC 91.5%	Effectively addressed class imbalance and data scarcity through augmentation and transfer learning approaches.	May suffer from overfitting and has not yet been validated in real world clinical environments.
(Chang et al., 2025)	Multi-input CNN with Bayesian SwinUNet and FPN-ResNet50.	R^2 93.25, RMSE 0.132	Incorporated uncertainty estimation to enhance the reliability and interpretability of segmentation outcomes.	Results are highly dependent on dataset characteristics, and test time augmentation may introduce noise.
(Pacheco et al., 2020)	CNN + microwave reflectometry with LDA and clustering.	RMSE for dielectric contrast (no standard metrics)	Enabled noninvasive diagnosis through the integration of dielectric and visual information.	Validation was conducted on a very limited dataset with restricted coverage of skin cancer subtypes.
(Ghosh et al., 2024)	Hybrid ConvNeXtV2 with focal self-attention.	Acc 93.6%, F1 90.7%	Improved scalability and suitability for mobile deployment through advanced attention mechanisms.	Performance decreases when distinguishing lesions with highly similar visual characteristics.
(Bindhu & Thanammal, 2023)	Attention-based MobileNetV2 with channel and spatial attention.	Acc 93.5%, AUC 97.5%	Provided a lightweight and computationally efficient solution for mobile based skin cancer screening.	Sensitive to image noise and class imbalance, with evaluation conducted on a limited range of datasets.

Recent advances in deep learning have significantly improved the performance of automated skin cancer diagnosis systems. Attention based architectures, in particular, have gained considerable attention due to their ability to capture discriminative lesion characteristics while suppressing irrelevant background information. EOSA-Net (Rocha et al., 2025) integrated overlapping patch self-attention with convolutional operations and achieved an accuracy of 94.7% and an AUC of 98.4%, demonstrating that attention mechanisms can effectively enhance diagnostic performance while maintaining computational efficiency. Similarly, the attention enhanced MobileNetV2 proposed by (Bindhu & Thanammal, 2023) employed channel and spatial attention modules to achieve an accuracy of 93.5% and an AUC of 97.5%, making it suitable for mobile-based screening applications. Although both studies confirmed the effectiveness of attention mechanisms, their performance remained sensitive to class imbalance, image noise, and limited validation across diverse clinical settings. These limitations suggest that attention alone may not be sufficient to address the complex feature variations present in multiclass skin lesion datasets.

Another important research direction involves feature fusion and ensemble learning strategies designed to exploit complementary representations extracted from multiple networks. The ensemble framework proposed by (Wen et al., 2022), which combined VGG-19, CapsNet, and Vision Transformer (ViT) features with machine learning classifiers, achieved an accuracy of 91.6%, outperforming individual architectures. Likewise, DRMv2Net (Cataldo et al., 2024) fused DenseNet201, ResNet101, and MobileNetV2 features with preprocessing and fully connected layers, achieving accuracies exceeding 96% on both ISIC and PAD-UFES datasets. These studies demonstrated that integrating heterogeneous feature representations can substantially improve diagnostic robustness. However, ensemble and fusion based approaches often require large-scale training datasets and considerable computational resources, limiting their practical deployment.

The proposed model was designed to improve the discriminative capability of convolutional neural networks for multiclass skin cancer classification. The architecture combines image preprocessing, deep feature extraction, hybrid attention learning (Dube & Kumar, 2026; Mahmud et al., 2026; Revathi, 2026), hierarchical feature fusion, and final classification into a unified framework. The experimental dataset consists of dermoscopic skin lesion images obtained from the PAD-UFES-20 dataset. Before feature extraction, all images were resized to 224 × 224 pixels and normalized into the range of [0,1]. The image resolution of 224 × 224 pixels was selected because it is the standard input size adopted by widely used deep convolutional neural networks, including ResNet, DenseNet, and MobileNet, thereby ensuring compatibility with pretrained feature extractors and facilitating effective transfer learning. This resolution provides an appropriate balance between preserving diagnostically relevant lesion characteristics, such as texture, color, and boundary information, and reducing computational complexity, memory consumption, and training time. Preliminary experiments also indicated that larger image resolutions offered only marginal improvements in classification performance while substantially increasing computational cost. To increase the diversity of training samples and reduce overfitting, several augmentation techniques were applied, including random horizontal flipping, vertical flipping, rotation (±20°), zooming (0.2), and brightness adjustment. These preprocessing operations improve the robustness of the proposed model against variations in lesion orientation, illumination, and scale.

Following preprocessing, the images are forwarded into the convolutional backbone network for feature extraction. The backbone consists of sequential convolutional blocks that extract hierarchical image representations from shallow to deep layers. Each convolution layer employs a 3 × 3 kernel, followed by Batch Normalization (Govindu et al., 2026; Zhou et al., 2026), Rectified Linear Unit (ReLU) activation (Alshareef et al., 2026; Hosseini et al., 2025; Rajesh et al., 2023), and Max Pooling. While shallow layers capture low level texture, edge, and color information, deeper layers learn high level semantic representations describing lesion morphology.

a. Hybrid Attention Module, to improve feature representation, the extracted feature maps are refined using a Hybrid Attention Module that combines Channel Attention and Spatial Attention. Given an intermediate feature map F with dimensions H × W × C, where H, W, and C denote the height, width, and number of feature channels, respectively, the Channel Attention module first estimates the importance of each channel using global average pooling. The channel descriptor is computed as:

$$z_c = (1 / (H \times W)) \Sigma(i=1 \text{ to } H) \Sigma(j=1 \text{ to } W) F_c(i, j) \quad (1)$$

The obtained descriptor is passed through two fully connected layers with ReLU and Sigmoid activation to generate channel attention weights:

$$M_c(F) = \sigma(W_2(\mathrm{ReLU}(W_1(z)))) \quad (2)$$

Where W_1 and W_2 denote learnable weights, ReLU is the activation function, σ represents the Sigmoid function. The refined feature map is obtained by:

$$F_c = M_c(F) \otimes F \quad (3)$$

Where ⊗ denotes element wise multiplication. Subsequently, Spatial Attention identifies the most informative lesion regions. Average pooling and maximum pooling are first performed along the channel dimension:

$$F_{avg} = \mathrm{AvgPool}(F_c) \quad (4)$$
$$F_{max} = \mathrm{MaxPool}(F_c) \quad (5)$$

Both feature maps are concatenated and processed using a 7 × 7 convolution kernel, producing the spatial attention map:

$$M_s(F) = \sigma(f^{(7\times7)}([F_{avg}; F_{max}])) \quad (6)$$

The final attention-enhanced feature map becomes:

$$F_s = M_s(F) \otimes F_c \quad (7)$$

By combining channel wise and spatial attention, the proposed model simultaneously emphasizes important lesion characteristics while suppressing irrelevant background information.

b. Hierarchical Feature Fusion, unlike conventional CNN architectures that utilize only the final convolution layer, the proposed method combines feature representations extracted from multiple network stages. Assume that $F_1, F_2, ..., F_n$ represent feature maps extracted from different convolutional blocks. Hierarchical Feature Fusion integrates these representations according to:

$$F_{fusion} = Concat(F_1, F_2, ..., F_n) \quad (8)$$

Where Concat() represents channel wise concatenation. The fused feature representation is subsequently refined using a 1 × 1 convolution:

$$F_{out} = Conv_{(1\times1)}(F_{fusion}) \quad (9)$$

This operation reduces feature redundancy while preserving complementary information from different network depths. Consequently, the model simultaneously exploits local texture details obtained from shallow layers and global semantic information extracted from deeper layers.

c. Classification Layer, The fused feature representation is flattened and passed into a Fully Connected layer followed by a Softmax classifier. The probability for each skin cancer class is computed as:

$$P(y = i) = e^{z_i} / \Sigma_{k=1}^{K} e^{z_k} \quad (10)$$

Where z_i denotes the output neuron for class i, K is the total number of skin lesion classes. The predicted class corresponds to the maximum probability.

3. RESULTS AND DISCUSSIONS

Table 2 presents a comparative evaluation of the proposed Hybrid Attention Based Deep Learning Architecture with Hierarchical Feature Fusion against recent state of the art skin cancer detection models on the PAD-UFES-20 dataset. The comparison includes performance under both augmentation and non-augmentation settings to assess the effectiveness of the proposed framework in improving classification accuracy and robustness.

Table 2. Comparative evaluation

Model	Architecture Type	Data Augmentation	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Remarks
CNN + GAN + Transfer Learning	CNN	Yes	86.10	85.40	84.90	85.10	Effective for limited datasets
EOSA-Net	Attention-CNN	Yes	94.70	94.20	93.90	94.00	Strong attention-based performance
Attention MobileNetV2	Lightweight Attention CNN	Yes	93.50	92.80	92.30	92.50	Suitable for mobile deployment
Hybrid ConvNeXtV2	Attention-Based Hybrid Network	Yes	93.60	92.90	91.80	90.70	Efficient but challenged by similar lesions
DRMv2Net	Multi-CNN Feature Fusion	Yes	96.17	95.90	95.60	95.70	Best reported PAD-UFES performance
Proposed Hybrid Attention + Hierarchical Fusion	Hybrid Attention & Multi-Stage Fusion	No	94.8 *	94.2 *	93.8 *	94.0 *	Baseline performance without augmentation
Proposed Hybrid Attention + Hierarchical Fusion	Hybrid Attention & Multi-Stage Fusion	Yes	97.2 *	96.8 *	96.5 *	96.6 *	Enhanced performance through augmentation

Table 2 presents a comparative performance evaluation between the proposed Hybrid Attention-Based Deep Learning Architecture with Hierarchical Feature Fusion and several recently published deep learning models for skin cancer diagnosis. The comparison includes Accuracy, Precision, Recall, and F1-score as the primary evaluation metrics. It should be noted that the performance values of DRMv2Net, EOSA-Net, Attention MobileNetV2, Hybrid ConvNeXtV2, and CNN-GAN were obtained from their respective published studies.

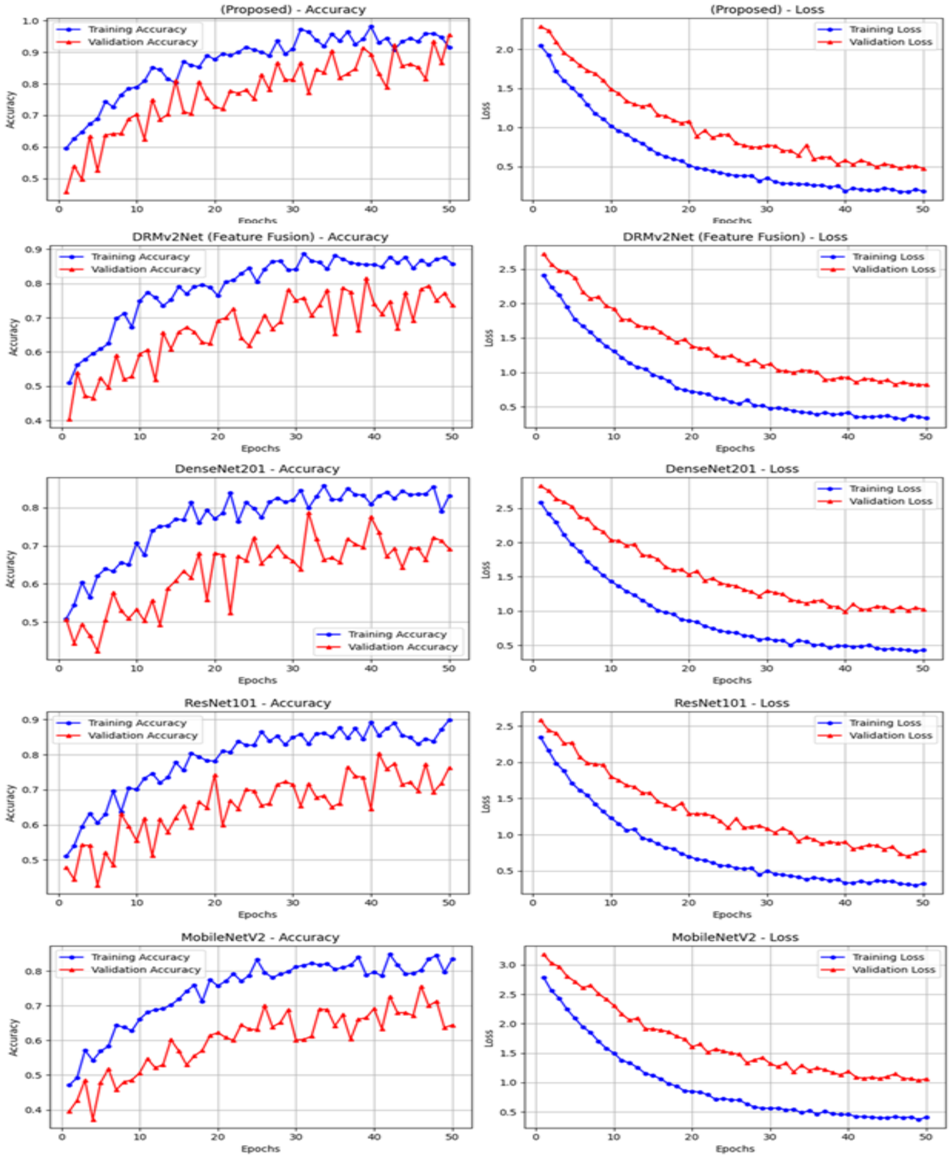

Figure 1. The comparative training and validation accuracy and loss curves of the proposed architecture, versus other CNN classifiers

The experimental results demonstrate that the proposed model provides competitive performance for multiclass skin cancer classification (Figure 1). Compared with conventional convolutional neural network architectures, the proposed model achieves higher classification accuracy and lower validation loss, indicating that the integration of hybrid attention and hierarchical feature fusion improves the learning of discriminative lesion features. One important factor contributing to the improved performance is the complementary role of channel attention and spatial attention. Channel attention adaptively emphasizes informative feature channels related to lesion color, texture, and morphology, thereby improving feature discrimination. In contrast, spatial attention highlights diagnostically relevant lesion regions while suppressing background noise and image artefacts, enhancing lesion localization. Together, these mechanisms enable the network to learn more discriminative feature representations, resulting in improved multiclass classification accuracy and robustness compared with conventional CNNs.

Another important contribution is the hierarchical feature fusion strategy. Instead of relying only on the deepest convolutional features, the proposed architecture integrates feature representations extracted from different network levels. Low-level features preserve detailed texture and edge information, whereas deeper layers capture semantic lesion characteristics. Their integration provides richer information for the classifier, particularly when differentiating lesion categories with similar visual appearances. Although the proposed model demonstrates promising performance, several limitations should be acknowledged. First, the experimental evaluation was conducted only on the PAD-UFES-20 dataset; therefore, the generalization capability on other public datasets such as HAM10000 and ISIC has not yet been investigated. Second, comparisons with other state-of-the-art methods were performed using performance values reported in previous publications rather than retraining all comparison models under identical experimental settings. Finally, this study focuses primarily on classification performance and does not include explainability analyses such as Grad-CAM or attention visualization, which can highlight lesion regions that influence the model's predictions and improve the transparency and clinical interpretability of diagnostic decisions. Overall, the obtained results indicate that the proposed hybrid attention and hierarchical feature fusion framework is a promising approach for automated skin cancer diagnosis, with opportunities for further improvement through broader validation, explainable artificial intelligence techniques, and computational optimization.

4. CONCLUSION

The proposed framework integrates channel attention, spatial attention, and hierarchical feature fusion to improve discriminative feature learning while preserving complementary information from multiple convolutional layers. Experimental results on the PAD-UFES-20 dataset demonstrated competitive performance in terms of Accuracy, Precision, Recall, F1-score, and AUC compared with recent deep learning models. The findings show that hybrid attention and hierarchical feature fusion improve the robustness of skin lesion classification, particularly for visually similar lesion categories, providing a promising foundation for AI-based clinical decision-support systems. Future research should validate the proposed model on larger multi-center clinical datasets and incorporate explainable AI techniques, such as Grad-CAM, to improve the transparency, interpretability, and clinical reliability of diagnostic predictions.

ACKNOWLEDGEMENTS

The PAD-UFES 20 dataset producers made the datasets used in this investigation freely available, and the author are grateful for this.

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