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Skin Disease Classification Algorithm Based on Multi-Scale Feature Decoupling and Boundary-Aware Diagnosis for Complex Lesion Morphology Recognition

Kewei Zeng
Northeastern University, San Jose, USA
zeng.kew@northeastern.edu

Abstract: Skin lesion images often present challenges due to complex color distributions, subtle texture variations, irregular edge morphology, and indistinct visual differences between different disease categories, posing a challenge to the stable recognition of automated classification models. To address the insufficient representation of complex lesion morphologies by single global features and the weakening of local diagnostic cues, this paper proposes a multi-scale feature decoupling and boundary-aware diagnostic algorithm for skin disease classification. This method first obtains lesion representations at different scales through hierarchical feature extraction, enabling shallow texture details and deep semantic information to jointly participate in classification modeling. Subsequently, a feature decoupling mechanism is constructed, dividing the mixed features into morphological, texture, and boundary-related subspaces to reduce redundant interference between different visual cues and enhance the model's ability to express the heterogeneous structure of lesions. Based on this, an adaptive scale fusion strategy is introduced to dynamically integrate features at different levels, allowing the model to highlight more discriminative scale responses based on sample feature differences. Simultaneously, a boundary-aware calibration module uses lesion contour and transition region information to spatially enhance the fused features, thereby improving the model's ability to recognize blurred boundaries, local diffusion, and irregular morphologies. Comparative experiments based on publicly available skin lesion image datasets show that the proposed method achieves superior performance in terms of accuracy, precision, recall, and F1 score, validating the effectiveness of the proposed algorithm in complex skin lesion classification tasks.

Keywords: Skin disease classification; multi-scale feature decoupling; boundary-aware diagnosis; lesion morphology recognition

1. Introduction

Skin diseases are a common and complex group of conditions in clinical practice, with their manifestations influenced by various factors such as lesion morphology, color distribution, texture structure, boundary state, and individual differences [1, 2]. Different skin diseases often exhibit strong visual similarities, while the same disease can show significant differences at different stages of development, on different body parts, and under different imaging conditions, leading to high uncertainty in lesion identification. Especially in scenarios with complex lesion morphology, the affected area may simultaneously exhibit significant scale variations, blurred edge transitions, uneven internal texture, and local structural abnormalities, making classification methods relying solely on overall visual representation insufficient to fully characterize the fine-grained differences in

the lesion area. Therefore, research on intelligent classification methods focusing on complex skin lesion morphology has significant clinical auxiliary diagnostic value and medical image analysis significance [3].

With the development of intelligent medical image analysis technology, deep learning methods have gradually become an important technical approach for auxiliary identification of skin diseases. Compared to traditional manual feature-based methods that rely on shallow descriptions such as color, texture, and shape, deep neural networks can automatically learn more discriminative high-level semantic features from images, providing a more effective modeling foundation for skin disease classification. However, key information in skin disease images is not always uniformly distributed across the entire lesion area; some lesion clues may be concentrated at fine edges, in localized patches, areas of color mutation, or areas of texture abnormality. If the model does not adequately represent information at different scales during feature extraction, or if it mixes lesion features, background interference features, and boundary structure features in its modeling, it can easily weaken the ability to recognize complex lesion morphologies, thus affecting the reliability and interpretability of the classification results [4].

Multi-scale feature modeling is an important direction for improving the classification performance of skin disease images. Skin lesions typically contain both global morphological contours and local detail changes. Global features help determine the overall shape, area distribution, and spatial structure of the lesion, while local features can reflect color deposition, texture roughness, edge irregularities, and subtle pathological signs. The diagnosis of complex lesions often requires the integration of visual evidence at different scales; single-scale features are insufficient to fully describe the heterogeneity of lesions. Therefore, through multi-scale feature extraction and decoupled modeling, morphological structure, texture details, and semantic discriminative information can be distinguished at different levels, reducing the interference of redundant features and irrelevant backgrounds on the model's judgment, allowing the classification model to focus more on key visual regions related to the disease category. Boundary information is also crucial in skin disease classification. The edge morphology, boundary clarity, and transition between lesions and surrounding normal skin often reflect the disease's progression and potential pathological features. For lesions with blurred boundaries, irregular shapes, or significant local spread, relying solely on internal texture information may not be sufficient to reveal diagnostic clues. Introducing a boundary-aware mechanism enhances the model's attention to changes in lesion contours and abnormal edge structures, enabling the classification process to rely not only on overall semantic features but also on fine-grained morphological expressions of lesion edges [5]. Therefore, researching skin disease classification algorithms that combine multi-scale feature decoupling with boundary-aware diagnosis for complex lesion morphology recognition can help improve the expressive power, discriminative ability, and clinical application potential of intelligent diagnostic models for complex skin disease images.

2. BackGround

Image analysis of skin diseases typically relies on a comprehensive understanding of the color, structure, texture, and morphological changes in lesion areas. Compared to natural image classification tasks, skin disease images are more medically specific and visually complex. Effective information for disease classification often exhibits localized, fine-grained, and non-uniformly distributed characteristics [6]. On the one hand, lesion areas can be affected by factors such as lighting differences, shooting angle, skin color, hair occlusion, and background noise, leading to significant fluctuations in image appearance. On the other hand, different categories of skin diseases may share similar color changes and texture patterns, while significant morphological changes may occur within the same category due to disease stage and individual differences. This inter-class similarity and intra-class variability jointly increase the modeling difficulty of automatic classification models, requiring models with stronger local perception and structural discrimination capabilities.

Existing deep learning methods provide an effective technical foundation for skin disease image classification. Convolutional neural networks can extract local texture and spatial structural features, while visual Transformer structures can enhance long-distance dependency modeling capabilities; both have shown strong

potential in medical image recognition tasks [7]. However, dermatological diagnosis relies not only on single-level semantic features but also requires simultaneous attention to the lesion itself, local abnormal regions, and boundary transitions. If the feature representation process lacks hierarchical modeling for complex morphologies, information at different scales can easily become aliased, and subtle lesion clues and marginal abnormal structures may be weakened by high-level semantic aggregation. Therefore, in dermatological classification research, constructing a feature representation mechanism that can simultaneously address global morphological understanding, local detail capture, and boundary structure perception has become a crucial fundamental issue for improving the diagnostic stability and medical interpretability of models.

3. Methodology

To address the problems of large-scale variation, uneven texture distribution, and ambiguous boundary transition in complex skin lesion morphology, this study constructs a skin disease classification model driven by multi-scale feature decoupling and boundary-aware collaboration, enabling the classification decision to jointly exploit lesion-level semantic information, local fine-grained differences, and contour structural cues. This paper also presents the overall model architecture, as shown in Figure 1.

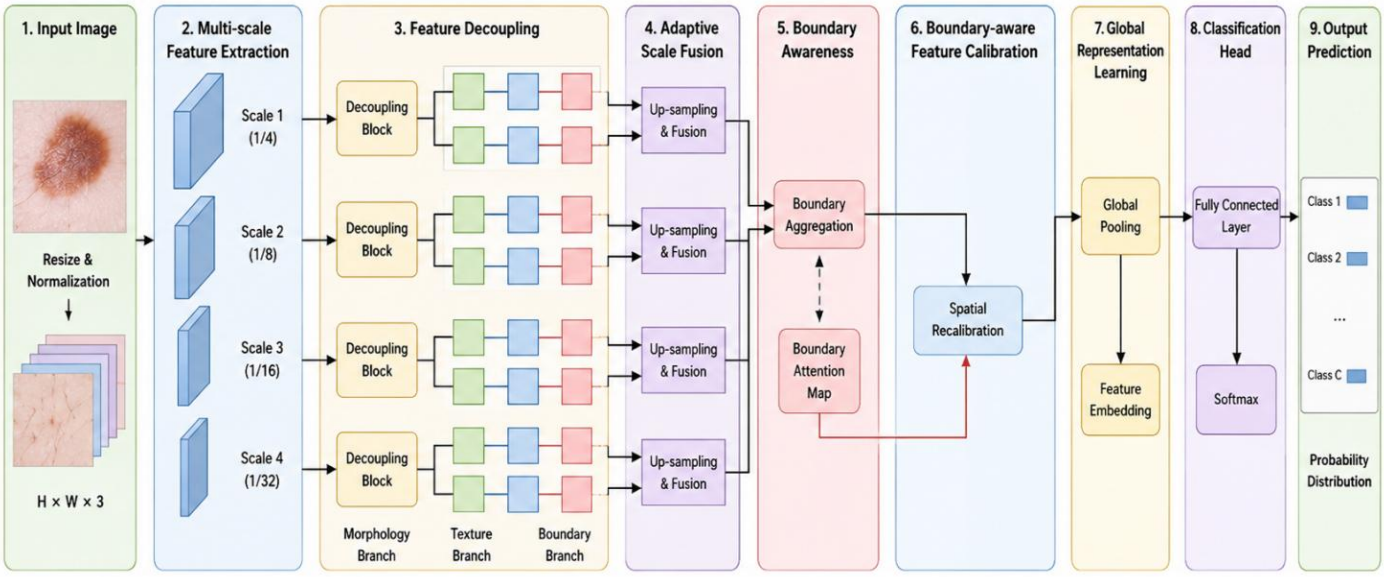

Figure 1. Overall model architecture

After unified size normalization, the input skin disease image is denoted as $\boldsymbol{I}$, and its pixel space and category space jointly form the basis for subsequent representation learning:

$$\boldsymbol{I} \in \mathbb{R}^{H\times W\times 3}, \quad y \in \{1,2,\ldots,C\}$$

The overall modeling process does not directly compress the image into a single global vector, but preserves spatial responses at different hierarchical levels to prevent early visual details from being excessively smoothed during deep semantic aggregation. The backbone network outputs feature tensors at multiple levels, where shallow features emphasize texture and edge variations, while deeper features tend to capture category semantics and global structures. The scale index s is embedded in the feature extraction process to maintain hierarchical differences:

$$\boldsymbol{F}_s = \mathcal{E}_s(\boldsymbol{I}), \quad s \in \{1,2,3,4\}$$

Such hierarchical representation extends lesion morphology recognition from single semantic discrimination to multi-granularity visual evidence integration, allowing the model to establish complementary relationships among global morphology, local plaques, and boundary transitions. For internal color deposition, texture

roughness, and morphologically irregular regions within lesions, relying only on deep semantic features may overlook local abnormalities; therefore, multi-scale features provide a more stable structural basis for subsequent decoupled modeling.

On the basis of multi-scale representation, this study further introduces a feature decoupling mechanism to decompose the mixed visual response at each level into three correlated but functionally distinct subspaces, namely morphological semantics, texture details, and boundary structure. The purpose of this design is not to simply increase the number of feature channels, but to reduce the representational entanglement among lesion body information, background interference, and contour information, so that different visual cues can play clearer discriminative roles in the classification process:

$$[\boldsymbol{M}_s, \boldsymbol{T}_s, \boldsymbol{B}_s] = [\mathcal{P}_m^s(\boldsymbol{F}_s), \mathcal{P}_t^s(\boldsymbol{F}_s), \mathcal{P}_b^s(\boldsymbol{F}_s)]$$

The obtained $\mathbf{M}_s$, $\mathbf{T}_s$, and $\mathbf{B}_s$ respectively encode the overall lesion morphology, local texture variations, and boundary response information. These three types of sub-features maintain complementarity within the same scale, while projection mappings are used to reduce the cross-interference of irrelevant responses. To enhance the representational independence among different subspaces, a decoupling constraint is embedded into the feature learning process, encouraging the morphology, texture, and boundary branches to reduce redundant similarity while preserving discriminative capability:

$$\mathcal{L}_d = \sum_{s=1}^{4} \left(\|\boldsymbol{M}_s^\top \boldsymbol{T}_s\|_F^2 + \|\boldsymbol{M}_s^\top \boldsymbol{B}_s\|_F^2 + \|\boldsymbol{T}_s^\top \boldsymbol{B}_s\|_F^2 \right)$$

This constraint encourages the model to allocate category-related evidence into clearer representation spaces, avoiding the formation of difficult-to-interpret black-box responses caused by mixing all discriminative information into a single pathway. After decoupling, the learned features no longer merely indicate whether a certain visual pattern exists in the image, but further characterize whether this pattern belongs to morphological contour, texture abnormality, or boundary structure, thereby improving semantic separability in complex lesion morphology recognition.

Considering that key diagnostic cues of skin lesions may be distributed across different spatial scales, this study adopts an adaptive scale fusion strategy to reorganize the decoupled multi-level information. The fusion process does not average all hierarchical features, but assigns weights according to the contribution of different scales to the current sample, enabling the model to dynamically emphasize scale responses with higher diagnostic value:

$$\boldsymbol{F}_{ms} = \sum_{s=1}^{4} \alpha_s \cdot \mathcal{U}_s(\boldsymbol{M}_s + \boldsymbol{T}_s), \quad \sum_{s=1}^{4} \alpha_s = 1$$

The scale weights α_s and the upsampling mapping $\mathcal{U}_s$ jointly act on the morphological and texture sub-features, allowing shallow details and deep semantics to be aligned under a unified resolution. Fine color mutations, local papular structures, and large-area plaque distributions in lesion images often affect disease judgment simultaneously, and adaptive fusion can avoid the omission of diagnostic cues caused by fixed-scale bias. On this basis, boundary structure is separately modeled as an attention response map to highlight the transition regions between lesions and surrounding normal skin:

$$\boldsymbol{A}_b = \sigma\left(\mathcal{C}_b\left(\sum_{s=1}^{4} \mathcal{U}_s\left(\boldsymbol{B}_s\right) \right) \right)$$

The generated $\mathbf{A}_b$ is obtained through the boundary convolution mapping $\mathcal{C}_b$ and the nonlinear activation function σ, and its role is to transform blurred edges, irregular contours, and locally diffused regions into explicit structural priors. This boundary prior does not directly replace classification features, but serves as a spatial modulation factor to enhance discriminative responses near lesion contours, allowing the model to consider external morphological changes while focusing on internal texture information.

At the diagnostic decision stage, the multi-scale fused features and boundary-aware information are jointly calibrated, so that the classification output is constrained by both lesion body semantics and edge structures. The fused feature is first spatially reweighted by boundary attention and then globally aggregated to obtain a sample-level representation, while the boundary modulation coefficient β controls the influence strength of contour structure on the final classification evidence:

$$\boldsymbol{z} = GAP(\boldsymbol{F}_{ms} + \beta \cdot \boldsymbol{A}_b \odot \boldsymbol{F}_{ms})$$

The final category probability is obtained through a classification mapping. Since $\mathbf{z}$ already contains cross-scale morphological information, local texture information, and boundary-enhanced information, it can provide a more complete diagnostic representation for complex lesion images:

$$\widehat{\boldsymbol{p}} = Softmax(\boldsymbol{W}_c\boldsymbol{z} + \boldsymbol{b}_c)$$

Compared with classification methods that rely only on global semantic compression, the proposed method reduces ineffective interference in mixed features through multi-scale decoupling and supplements diagnostic evidence at the lesion contour level through a boundary-aware mechanism. The model training objective consists of the category discrimination term, the feature decoupling term, and the boundary structure term, enabling the network to maintain structured representation constraints while optimizing classification capability:

$$\mathcal{L} = \mathcal{L}_{cls} + \lambda_d\mathcal{L}_d + \lambda_b\mathcal{L}_b$$

This optimization formulation prevents classification learning from being limited to label-supervised outcome fitting, and further guides the model to form separable, multi-scale, and boundary-sensitive representations for complex lesion morphology recognition, thereby enhancing the medical rationality and structural interpretability of skin disease classification.

4. Experimental Results and Analysis

4.1 Dataset

This paper uses the publicly available ISIC 2019 Challenge skin lesion image dataset as the research data source. This dataset is designed for multi-class classification of skin lesions. The training set contains 25,331 dermoscopic images and provides corresponding standard diagnostic labels, covering typical skin lesion categories such as melanoma, melanocytic nevus, basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, vascular lesions, and squamous cell carcinoma. In this study, healthy or non-lesion samples were excluded, and only lesion images with definite diagnostic labels were retained for model training and evaluation. Meanwhile, the boundary-related structural information used in the boundary-aware module was generated by Sobel edge detection, which provides explicit contour cues without requiring additional manual boundary annotations. This dataset has strong category complexity and morphological diversity. Different lesions show significant differences in color distribution, texture patterns, boundary clarity, and local structure. At the same time, some categories have high visual similarity, which can well support the research on complex lesion morphology recognition, multi-scale feature decoupling, and boundary-aware diagnostic methods. Since the ISIC 2019 dataset contains a large number of dermoscopic images, standardized category labels, and a publicly available download link, its data scale and task setting are highly consistent with the research goal of this paper, which focuses on the classification of complex skin diseases.

4.2 Experimental Setup

To ensure the stability and consistency of the model training process, all experiments were conducted in a unified deep learning environment. Input skin lesion images were uniformly adjusted to a fixed resolution and normalized before training. The AdamW optimizer was used for model training, with cross-entropy loss as the primary classification supervision, combined with feature decoupling constraints and boundary structure constraints to optimize network parameters. A cosine annealing strategy was used for learning rate scheduling to mitigate parameter oscillations in the later stages of training and improve model convergence stability. A fixed random seed was set during training to reduce the random impact of data partitioning, parameter initialization, and batch sampling. The main hardware and software environment and key parameter settings used in this experiment are shown in Table 1.

Table 1. Experimental environment and hyperparameter settings

Configuration Item	Specific Setting
Operating System	Ubuntu 20.04 LTS
CPU	Intel Xeon Silver 4214
GPU	NVIDIA A100 40GB
CUDA Version	CUDA 11.8
Programming Language	Python 3.10
Deep Learning Framework	PyTorch 2.1
Image Processing Libraries	OpenCV, Pillow
Model Construction Libraries	Torchvision, Timm
Input Image Size	224 × 224
Batch Size	32
Training Epochs	100
Optimizer	AdamW
Initial Learning Rate	1e-4
Weight Decay	1e-4
Learning Rate Scheduling Strategy	Cosine Annealing
Loss Function	Cross Entropy Loss + Decoupling Loss + Boundary Loss
Dropout Rate	0.3

4.3 Experimental Results and Analysis

For the task of recognizing complex skin lesion morphology, relevant comparative methods mainly come from research directions such as dermoscopic image classification, intelligent diagnosis of skin cancer, and deep convolutional feature learning. To maintain consistency between the comparison objects and the method in this paper, the comparison scope focuses on deep learning classification models based on publicly available skin lesion images, and representative studies are selected as references from the perspectives of global semantic modeling, transfer learning, multi-resolution ensemble, and convolutional feature enhancement to demonstrate the method positioning of the multi-scale feature decoupling and boundary-aware diagnostic mechanism in complex lesion recognition scenarios. The experimental results are shown in Table 2.

The comparative results in Table 2 indicate that the proposed method delivers the strongest overall performance across all four evaluation metrics, with ACC, PRE, REC, and F1 scores reaching 94.35%, 93.68%, 92.94%, and 93.31%, respectively, outperforming existing methods. Compared to Gessert et al., whose performance is closest, the proposed method improves ACC, PRE, REC, and F1 scores by 2.19, 2.25, 2.22, and 2.24 percentage points, respectively, indicating that the multi-scale feature decoupling and boundary-aware diagnostic mechanism effectively enhances the model's ability to discriminate complex skin lesion morphologies. Compared to earlier methods, the proposed method maintains high precision and recall, demonstrating that the model not only reduces the risk of misclassification between different lesion categories but also more effectively identifies lesion samples with fine-grained texture differences and blurred boundary features. In

summary, the results validate the effectiveness and stability of the proposed method in skin disease classification tasks, especially demonstrating its advantages in complex morphological modeling, local anomaly capture, and boundary structure utilization.

Table 2. Comparative results of related methods and the proposed method

Method	ACC (%)	PRE (%)	REC (%)	F1 (%)
Esteva et al. [8]	86.27	85.73	84.91	85.18
Lopez et al. [9]	84.16	82.94	81.68	82.30
Haenssle et al. [10]	87.03	86.12	85.67	85.89
Kassani et al. [11]	88.64	87.35	88.07	87.71
Hosny et al. [12]	89.21	88.96	87.88	88.41
Albahar et al. [13]	90.38	89.54	89.11	89.32
Gessert et al. [14]	92.16	91.43	90.72	91.07
Ours	94.35	93.68	92.94	93.31

To further analyze the contributions of multi-scale feature decoupling, boundary-aware modeling, and scale fusion strategies to the classification of complex skin lesions, this paper constructs ablation settings around the core components of the method and compares the classification performance of different configurations under a unified evaluation metric. Table 3 shows the performance changes after each module is removed, reflecting the roles of different structures in lesion semantic modeling, local texture differentiation, and boundary structure utilization.

Table 3. Ablation study of the proposed method

Ablation Setting	ACC (%)	PRE (%)	REC (%)	F1 (%)
w/o Multi-Scale Feature Decoupling	91.82	91.05	90.44	90.74
w/o Adaptive Scale Fusion	92.48	91.76	91.13	91.44
w/o Boundary-Aware Calibration	92.06	91.28	90.91	91.09
Ours	94.35	93.68	92.94	93.31

The ablation comparison further demonstrates that the complete model consistently achieves the strongest performance across ACC, PRE, REC, and F1, confirming the effectiveness of the integrated design. This indicates that multi-scale feature decoupling, adaptive scale fusion, and boundary-aware calibration are the key factors contributing to the improved model performance. When multi-scale feature decoupling was removed, the model's F1 score dropped to 90.74%, a decrease of 2.57 percentage points compared to the complete model. This suggests that a lack of clear separation between morphological, textural, and boundary information can easily lead to the overlapping of heterogeneous lesion features, weakening the ability to classify complex morphologies. After removing adaptive scale fusion, ACC and F1 scores decreased to 92.48% and 91.44%, respectively, demonstrating the crucial role of dynamic integration of features at different levels in balancing global lesion structure with local detail changes. After removing boundary-aware calibration, the overall model performance also showed a significant decline, especially in REC and F1, which dropped to 90.91% and 91.09%, respectively. This indicates that boundary structure information can effectively enhance the model's ability to perceive blurred contours, irregular edges, and localized diffusion areas. In summary, all three modules contribute positively to the final classification performance, with multi-scale feature decoupling having the most significant impact, further validating the necessity of structured feature representation in the identification of complex skin lesions.

As shown in Figure 2, both training and validation losses exhibit a continuous decreasing trend over 100 epochs, indicating that the model can gradually learn effective discriminative features in skin lesion images during iteration and continuously optimize the classification boundaries. The loss decreases rapidly in the early stages of training, suggesting that the network can quickly capture the basic morphology, color, and texture information of lesions. As training progresses, the rate of loss decreases gradually diminishes, and the model

enters a relatively stable refinement and optimization phase. The validation loss is generally higher than the training loss, with some fluctuations, reflecting issues such as inter-class similarity, blurred boundaries, and complex local texture differences in skin lesion images. However, its overall decreasing trend is consistent with the training loss, indicating that the model does not exhibit significant overfitting. In the later stages, both training and validation losses remain at low levels, indicating that the constructed model has good convergence stability and generalization ability.

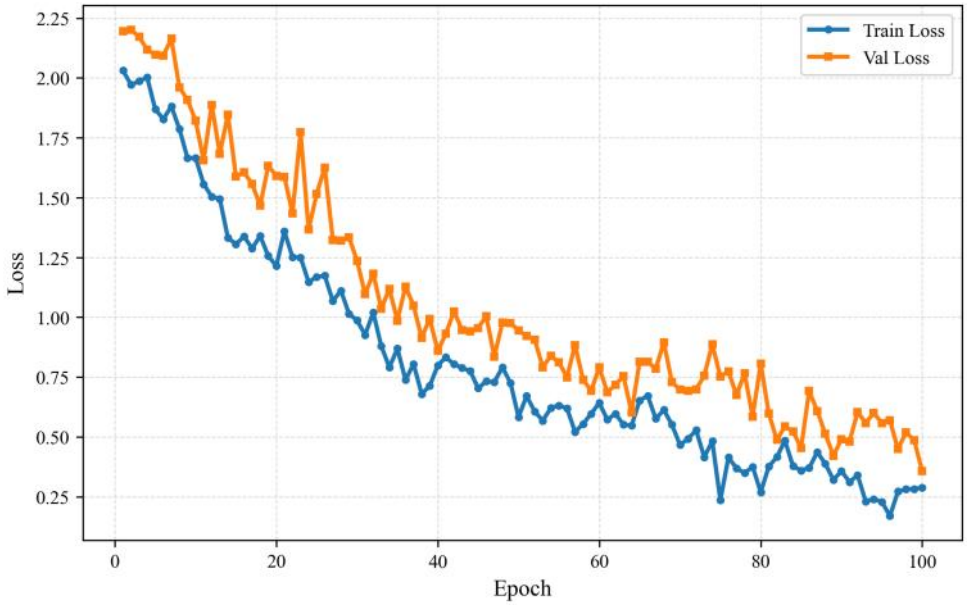

Figure 2. Image showing how the loss function changes with the epoch

The two-dimensional t-SNE visualization in Figure 3 reveals that the eight types of skin lesion samples exhibit a relatively clear category clustering structure in the feature space. The sample points corresponding to different colors are mostly distributed in relatively independent regions, indicating that the deep features learned by the model have strong inter-class discrimination capabilities. Categories such as MEL, NV, BCC, AK, BKL, DF, VASC, and SCC all exhibit obvious clustered distributions, indicating that the multi-scale feature decoupling mechanism can effectively extract discriminative information related to lesion morphology, texture, and boundaries, maintaining high consistency among samples of the same category in the feature space. Some categories contain several local sub-clusters, reflecting differences in color representation, lesion scale, and edge morphology within the same skin lesion category. However, these sub-clusters mainly remain within their respective category ranges, indicating that the model has good tolerance for intra-class morphological variations. Overall, Figure 3 verifies that the proposed method can enhance the feature separability of complex skin lesion images and provide a stable representational basis for subsequent classification decisions.

Figure 4 shows that the Grad-CAM visualization results can intuitively reflect the model's focus areas during skin disease classification. The thermal response is mainly concentrated in the lesion body, the erythema diffusion area, the pigment deposition area, and the local boundary transition area, rather than being widely distributed in the irrelevant background. This indicates that the model's classification criteria are well consistent with the key visual features of skin lesions. The high-response areas show some differences among different samples, indicating that the model can adaptively capture discrimination cues based on lesion morphology and texture. For example, inflammatory areas, uneven pigmentation areas, and abnormal edge areas all show strong activation. The overlay image further shows that the model not only focuses on the central area of the lesion but also covers part of the boundary and surrounding transition structures, which is consistent with the multi-scale feature decoupling and boundary-aware calibration mechanism introduced in this paper.

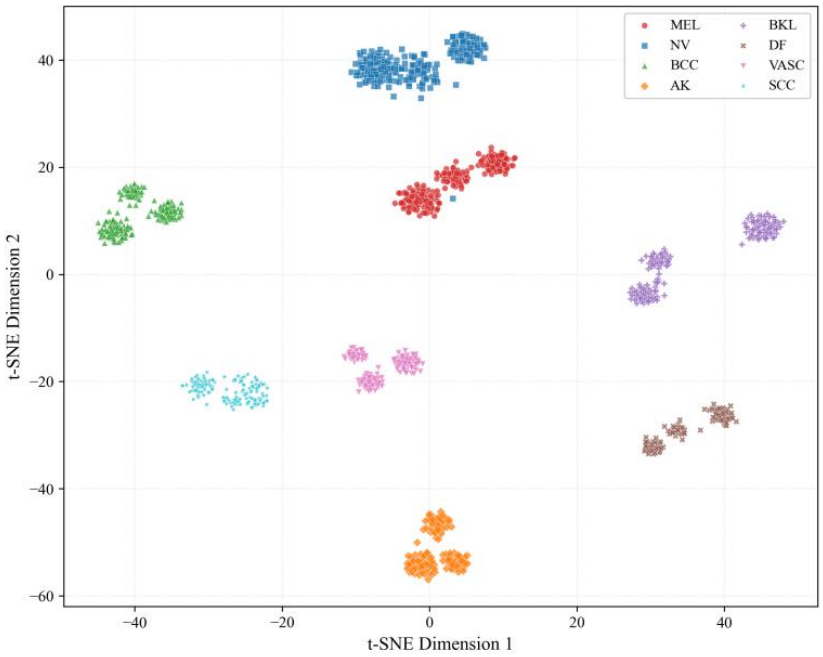

Figure 3. t-SNE experimental results

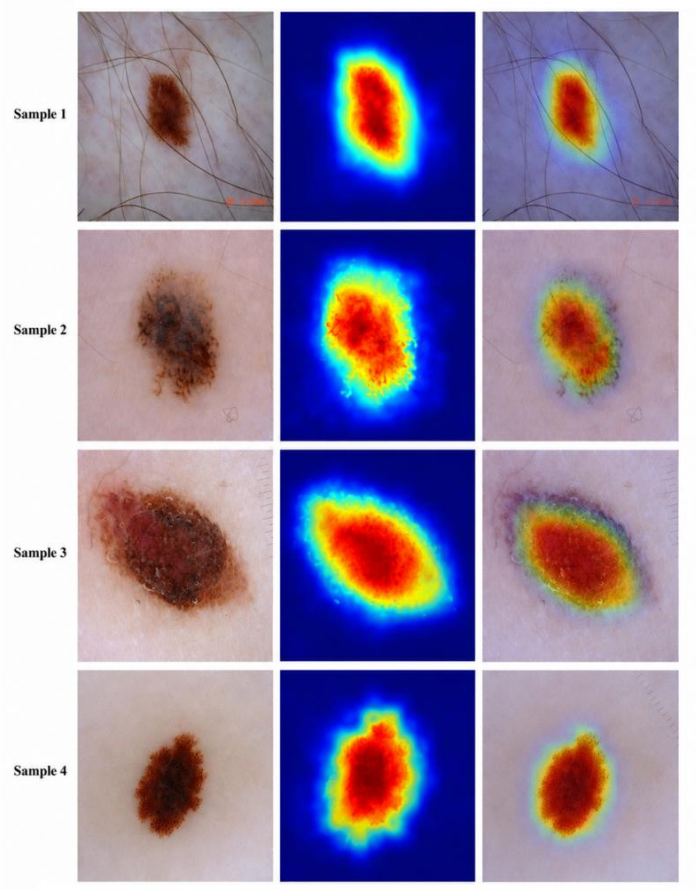

Figure 4. Grad-CAM experimental results

5. Conclusion

This paper addresses key challenges in complex skin lesion morphology recognition, including significant scale differences, uneven local texture, blurred boundary transitions, and visual similarity between categories. It proposes a skin disease classification algorithm that integrates multi-scale feature decoupling and boundary-aware diagnosis. This method no longer treats skin lesion images as a single global semantic object, but instead constructs more detailed feature representations from three levels: the lesion's main morphology, local texture differences, and boundary structure changes. This allows the model to capture more medically meaningful discriminative cues in complex lesion images. The multi-scale feature decoupling mechanism enhances the model's ability to organize visual evidence at different scales, reducing the mixed interference between morphological, texture, and boundary information. The boundary-aware calibration mechanism further strengthens the model's focus on lesion contours, edge irregularities, and local transition regions, enabling the classification process to more fully utilize the diagnostically valuable structural information in skin disease images. Overall, this method provides a more structured, interpretable, and medically oriented modeling approach for complex skin lesion classification.

Comparative results show that the proposed method achieves superior overall performance in skin lesion classification tasks, indicating that the combination of multi-scale feature decoupling and boundary-aware diagnosis effectively improves the model's ability to recognize complex lesion morphologies. Compared to classification methods that rely solely on global feature aggregation, this method better handles common intra-class differences and inter-class similarities in skin disease images. It can still form relatively stable discriminative representations even when faced with uneven color distribution, subtle texture details, unclear lesion boundaries, and irregular local abnormal areas. This research has certain application value for intelligent assisted diagnosis of skin diseases, providing technical support for clinical screening, primary healthcare auxiliary judgment, remote skin disease image analysis, and intelligent management of medical images. By improving the model's understanding of complex lesion morphologies, the method helps reduce subjective differences in the human observation process, providing a more objective, stable, and scalable intelligent analysis tool for skin disease classification tasks.

Future research can further expand on the data complexity and application reliability in real-world clinical scenarios. On the one hand, skin disease images may exhibit significant distributional differences under varying acquisition devices, lighting conditions, imaging distances, and individual skin characteristics. Further improvements can be made to enhance the model's generalization ability across devices, centers, and multi-source data conditions, making it more adaptable to complex inputs in real-world medical environments. On the other hand, intelligent diagnostic systems for skin diseases not only need high classification performance but should also enhance their ability to interpret lesion regions, boundary structures, and key visual evidence, thereby improving credibility and acceptability in clinical use. With the development of multimodal medical data and intelligent diagnostic platforms, future research could also integrate dermoscopic images, clinical descriptions, medical history information, and physicians' prior knowledge to construct a more comprehensive intelligent auxiliary diagnostic framework for skin diseases. Continued advancement in this direction will help improve the efficiency of skin disease screening, optimize the allocation of medical resources, and promote the in-depth application of medical image artificial intelligence technology in actual diagnostic and treatment processes.

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