

# Deep adaptive feature blending system for automated nail disease detection

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## ABSTRACT

Nail diseases present significant diagnostic challenges due to their wide variability in visual appearance, overlapping morphological characteristics, and often subtle early-stage symptoms. Conventional diagnosis largely relies on subjective assessment by dermatology specialists, which can be time-consuming and prone to inter-observer variability. This limitation is particularly critical for serious conditions such as acral lentiginous melanoma, where delayed or inaccurate detection may lead to suboptimal clinical outcomes. To address these challenges, this study proposes a deep learning framework termed deep adaptive feature blending (DAFB). The approach integrates the EfficientNetV2-S architecture with an AFB module that recalibrates discriminative features to improve classification performance. The AFB mechanism employs a dual-path attention strategy that emphasizes salient visual patterns while suppressing noise and irrelevant artifacts commonly present in dermatoscopic nail imagery. When evaluated on a multi-class nail disease dataset, the DAFB model achieved a validation accuracy of 97.8%, demonstrating strong performance across all disease categories. Experimental results indicate that the framework is effective in distinguishing between morphologically similar conditions while maintaining computational efficiency. However, given the limited dataset size and lack of external validation, these results should be interpreted as preliminary. Overall, the proposed approach shows promising potential as a research-oriented tool for automated nail disease classification, warranting further validation on larger, more diverse clinical datasets.



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## 1. Introduction

Nail diseases are common medical issues and can often indicate other conditions, such as infections or autoimmune diseases. Therefore, identifying and accurately diagnosing nail diseases is critical in providing the best possible treatment options for patients. However, current methods for diagnosing nail diseases primarily rely on a doctor’s visual inspection. Visual identification by doctors is inherently subjective and prone to inconsistency.<sup>1,2</sup> Factors such as lighting, skin color, image quality, and disease severity all contribute to inconsistency and increase the likelihood of inaccurate diagnoses, especially at the beginning of a disease when only slight changes in the appearance of the nails can occur, such as changes in color or texture.<sup>3,4</sup> Recent advances in machine learning, particularly deep learning algorithms, have greatly impacted medical image processing and analysis by enabling the development of computer-based systems capable of classifying images according to specific criteria in dermatology and other areas of medicine.<sup>5,6</sup> Nonetheless, several specific problems arise when applying deep learning to the classification of nail diseases. These include: (i) sampling efficiency, where important information may be lost, and subsequently affect the accuracy of the classification process; (ii) computational and memory usage, limiting the capability of deploying these systems on low-resource hardware; and (iii) lack of interpretability, making it difficult for clinicians to place their confidence in the classifications, and provide transparent decision-making.<sup>7,8</sup>

Moreover, two additional problems, which are unique to nail diseases, complicate the development of robust, automatic systems to classify nail diseases: (i) the subtlety of early-stage manifestations of nail diseases, increasing the likelihood of misclassifications; and (ii) the lack of standardization and diversity in available datasets of images of the nails, causing the inability to generalize due to the heterogeneity of images in terms of light sources, and the variety of nail diseases.<sup>9,10</sup> We introduce a novel expert system, the deep adaptive feature blending (DAFB) framework, for automated classification of nail diseases. Our architecture combines the EfficientNetV2-S backbone featuring a very scalable and efficient convolutional neural network (CNN), together with a newly developed AFB module, which has been specifically constructed to enhance both feature discrimination and

model interpretability.<sup>11,12</sup> The AFB module uses a dual-path attention mechanism that dynamically recalibrates the hierarchical features within the model, while enhancing relevant pathological patterns and suppressing irrelevant noise and background artifacts typically observed in dermoscopic nail images. To improve the robustness and generalization of the model, extensive data augmentation techniques have been applied, including random flips, color jittering, and rotations, during training to enhance the real-world variability in imaging. The main contributions of this study are summarized as follows:

- (i) Introduction of the DAFB Framework: Development of a novel end-to-end deep learning pipeline for multi-class nail disease classification, and integration of the EfficientNetV2-S backbone with a lightweight and scalable AFB module.
- (ii) Design of the AFB module: Implementation of a dual-path attention mechanism for dynamic feature recalibration, and enhanced separation of clinically relevant patterns from background noise, improving diagnostic accuracy and interpretability.

The rest of this paper is organized as follows: Section 2 reviews the related work. Section 3 describes the proposed model and methodology. Section 4 details the experimental results. Section 5 concludes the paper and highlights future research directions.

## 2. Related work

Nail disorders can provide early warnings of potentially serious diseases; hence, an accurate diagnosis is essential if the diseases are to be easily identified and combatted.<sup>1,13</sup> The relevant literature can be shown in the following studies bearing on the potential for deep learning and artificial intelligence to revolutionize the diagnosis and management of such nail disorders<sup>14,15</sup> (**Table 1**). Shandilya *et al.*<sup>16</sup> discussed the creation of deep learning algorithms for the automatic classification of nail disorders based on image data. This work began with a baseline convolution neural net model, followed by the development of a hybrid capsule convolution neural net model<sup>17,18</sup>, designed to better capture hierarchical spatial relationships and structural variations. The hybrid CNN model outperformed previous models, achieving training and validation accuracies of 99.40%. In

addition, the model improved the effectiveness with which transformations are handled and the spatial properties. This methodology offers a workable, inexpensive, and readily available diagnostic technique in healthcare settings. Gaurav *et al.*<sup>8</sup> presented a literature review on artificial intelligence (AI) in nail disorders and found that the use of deep CNNs has been shown to possess sensitivity and specificity in the interpretation of degrading information of nails, which improved differential diagnosis. AI systems have been used to detect subungual melanoma, perform automated disease severity scoring, and even assist with nailfold capillaroscopy. AI is also helpful in addressing nail disorders by providing treatment modalities, personalized treatment planning, remote care, and monitoring. Ardianto *et al.*<sup>19</sup> considered the use of CNNs for nail disorders, such as onychomycosis. They used a database of 655 nail images, and the CNN model achieved a success rate of 83%, but requires remodeling for underrepresented classification. A user-friendly interface for quick diagnosis was also an aim. Hamim *et al.*<sup>7</sup> employed image processing and deep learning data to improve models for nail disease detection. Images with bluish fingernails, red, puffy nails, and yellow fungal nails had post-testing success rates of 92%, 72%, and 89%, respectively.

Hussain *et al.*<sup>20</sup> presented a new dataset for training and evaluating deep learning algorithms for the localization of nail melanoma. Seven CNN-based deep learning architectures were trained and validated for skin lesion classification from dermatoscopic imagery datasets, achieving accuracies of >95% and results that would certainly yield quantifiable results for use on memory-constrained mobile/edge devices. It would considerably improve the diagnosis of skin melanoma and enable earlier, faster evaluation of the condition compared with other malignant forms of skin cancer. Sechi *et al.*<sup>5</sup> explored techniques of imagery, especially in nail disorders, and their clinical utility. The high-resolution camera and dermoscope enabled early disease diagnosis and monitoring. Advanced imaging systems such as ultrasound, magnetic resonance imaging, and confocal microscopy have been adopted for diagnostic purposes. Notably, there is a strong need for proper training, rigorous validation, and regulatory oversight in the application of technology to healthcare.<sup>21-25</sup>

### 3. Methodology

This section presents the architectural design and training strategy, followed by the evaluation methodology for the proposed DAFB framework, illustrated schematically in **Figure 1**. The DAFB framework has been developed in direct response to the diagnostic complexities outlined in Section 1 and uses a hybrid convolutional-transformer architecture tailored for the complex task of nail disease classification.<sup>26-29</sup> By combining convolution and self-attention, the architecture allows simultaneous focus on fine-detail local features and global contextual dependencies, as required for differentiating visually similar patterns of disease. The architecture's design has demonstrated the ability to optimize the balance between discriminative capacity and computational efficiency, rendering it suitable for application in real-world clinical settings where resources may be limited.<sup>30-33</sup>

#### 3.1. Dataset description

The dataset used in this study comprises a structured, diverse set of dermoscopic nail images for automated disease classification, as illustrated in **Figure 2** and summarized in **Table 2**. The dataset consists of six clinically relevant classes, with each class represented by a separate subfolder containing a set of labeled images. This partitioning strategy was adopted to ensure a balanced representation of all disease categories across the training and validation sets. The dataset used in this study is publicly available on Kaggle and was pre-partitioned by the dataset provider into training and validation subsets. Specifically, the training set consists of 3,744 images, and the validation set contains 91 images, for a total of 3,835 images across six classes. The hyperparameters of the adaptive moment estimation with decoupled weight decay optimizer are illustrated in **Tables 3** and **4**.

#### 3.2. Preprocessing and data augmentation

The objective of this operation was to improve the quality and conformity of the input images for the neural network by applying a large preprocessing pipeline to all images prior to the training of the neural net and includes:

- (i) Normalization: All images were treated equally, their size was altered to  $224 \times 224$  pixels, and then adaptive histogram

**Table 1.** Summaries of recent studies classifying nail diseases using deep learning techniques

| Authors                               | Focus                                                     | Methodology                                                               | Results                                                                                                                          |
|---------------------------------------|-----------------------------------------------------------|---------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------|
| Shandilya <i>et al.</i> <sup>16</sup> | Autonomous detection of six nail disorders using images   | Hybrid capsule CNN model                                                  | Achieved 99.40% training and validation accuracy; enhanced robustness against transformations and spatial properties             |
| Gaurav <i>et al.</i> <sup>8</sup>     | AI applications in diagnosing and managing nail disorders | Literature review focusing on deep CNNs                                   | Found high sensitivity and specificity in interpreting nail images; AI aids in differential diagnosis and enhances efficiency    |
| Ardianto <i>et al.</i> <sup>19</sup>  | Identification of nail disorders, such as onychomycosis   | CNN model trained on a dataset of 655 nail photos                         | Achieved 83% accuracy; highlighted need for improvement in underrepresented classifications                                      |
| Hamim <i>et al.</i> <sup>7</sup>      | Detection of diseases in human nails                      | A combination of image processing techniques and deep learning algorithms | Models for bluish fingernails, red puffy nail, and yellow fungal nail achieved accuracy rates of 92%, 72%, and 89%, respectively |
| Hussain <i>et al.</i> <sup>20</sup>   | Nail melanoma localization                                | Development of “Nailmelonma” dataset; trained seven CNNs                  | Models achieved over 95% accuracy; quantization suitable for memory-constrained mobile/edge devices                              |

Abbreviations: AI: Artificial intelligence; CNN: Convolutional neural network.

**Table 2.** The dataset structure description

| Category                   | Description                                     |
|----------------------------|-------------------------------------------------|
| Acral lentiginous melanoma | A rare type of melanoma affecting nails         |
| Healthy nail               | Normal, non-diseased nail images                |
| Onychogryphosis            | Thickened, curved nail disorder                 |
| Blue finger                | Nail discoloration due to circulation issues    |
| Clubbing                   | Rounded, enlarged nails linked to health issues |
| Pitting                    | Small depressions or pits in the nail surface   |

equalization was applied to render all images’ contrast and visibility of features equal (**Equation 1**).

$$I_{norm} = \frac{I - \mu}{\sigma}, \mu = [0.485, 0.456, 0.406], \sigma = [0.229, 0.224, 0.225] \quad (1)$$

(ii) Artefact removal: Non-local means denoising was applied to the images to reduce speckle noise and remove artifacts such as hairs and glare reflections.

(iii) Data augmentation: Data augmentation was performed dynamically throughout the training of the neural network.<sup>34-36</sup> A combination of geometric and photometric techniques, including handling specular highlights, enabled the neural network to generalize across varying imaging conditions and anatomical differences.

The input images were resized to  $224 \times 224$  and underwent the following transformations: random horizontal flip, random vertical flip, color jitter (brightness, contrast, saturation, hue variations), random rotation ( $\pm 20$  degrees), and normalization<sup>21</sup>, as shown in **Figure 3**.

### 3.3. Model architecture

**Figure 4** shows the number of images per subject in both the training and validation sets, with the

majority in the training set. The framework was designed to provide high discriminative power with a low computational cost, necessary for deployment as a clinical decision support system.

The EfficientNetV2-S backbone was pretrained on the ImageNet dataset to serve as the primary feature extractor.<sup>37-39</sup> This state-of-the-art CNN employs compound scaling, which optimally scales the depth, width, and resolution of the network to achieve maximum performance with minimum computational effort. This results in the representation of multi-scale high-level semantic features using EfficientNetV2-S when applied to nail disease images, specifically summarizing the numerous visual characteristics of nail disease. To increase the quality and relevance of the extracted feature representations, we introduced the AFB module, a low-cost attention-based mechanism that adaptively recalibrates the feature maps. The module learns the attention weights of the feature maps, increasing the representation of discriminative features whilst reducing that of non-discriminative background noise and artifacts prevalent in clinical dermoscopic images.<sup>40-42</sup> This adaptive blending ensures that only the most discriminative features are passed to the classifier head, thereby improving both the accuracy and interpretability of the model. Let  $F \in \mathbb{R}^{C \times H' \times W'}$  be the feature map obtained from EfficientNetV2-S. The AFB module used two convolutional layers to compute attention weights (**Equation 2**):

$$A = \sigma(\text{Conv1}(F)) \quad (2)$$

where  $A \in \mathbb{R}^{C \times H' \times W'}$  is the attention map, and  $\sigma(\cdot)$  is the sigmoid activation function, ensuring that the attention map values range from 0 to 1. The AFB operation then applied the learned attention weights to the input feature map:

$$F_{\text{blended}} = F \times A + F \quad (3)$$

where  $F_{\text{blended}}$  is the resulting feature map after the blending operation, and each element in  $F$  is scaled by the corresponding attention weight from  $A$ . This operation allowed the network to focus more on the image's important regions while preserving the original features.

### 3.3.1. Adaptive feature blending module design

Dual-path attention was employed, consisting of parallel spatial and channel attention branches that compute complementary attention maps.

The spatial branch used deformable convolutions to focus on irregular nail margins, while the channel branch captured cross-scale dependencies through grouped convolutions. A dynamic fusion mechanism then adaptively combined the spatial and channel attention maps using a learnable gating function (**Equation 4**):

$$F_{\text{out}} = \sigma(W_g F_{\text{spatial}} \oplus F_{\text{channel}}) \odot F_{\text{in}} \quad (4)$$

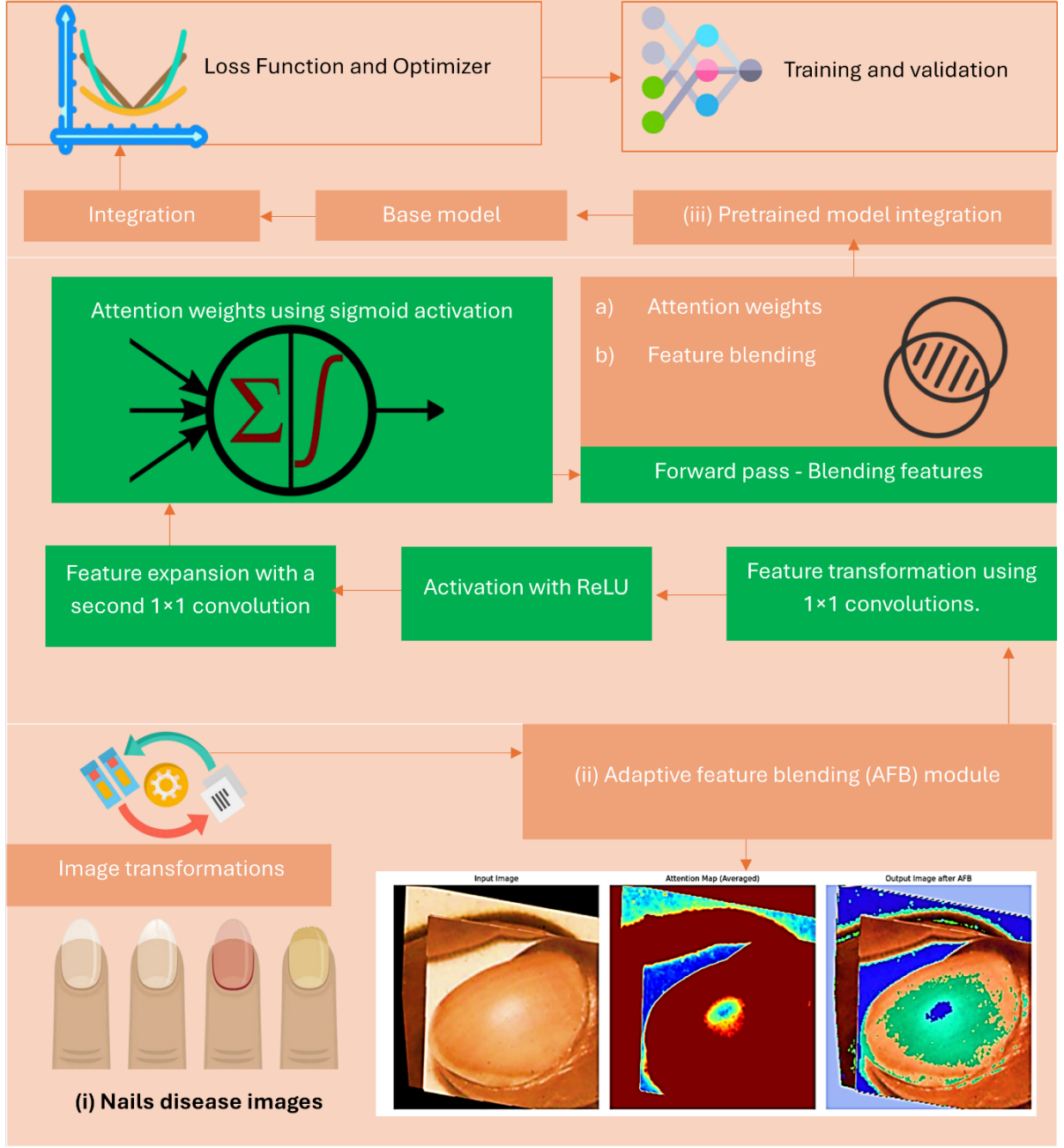
where  $W_g$  denotes a  $1 \times 1$  convolution,  $\oplus$  is concatenation, and  $\odot$  is element-wise multiplication.

The classification head with blended features was pooled hierarchically and fed into a multi-task classifier with a softmax function. The training stage had a hybrid focal loss (for class imbalance) and Kullback–Leibler divergence to penalize overconfidence.<sup>27,28</sup> The formulation represents a weighted combination of two loss components: the focal loss and the Kullback–Leibler divergence loss (**Equation 5**).

$$\mathcal{L} = \lambda_1 \mathcal{L}_{\text{focal}} + \lambda_2 \mathcal{L}_{\text{KL}} \quad (5)$$

where  $\mathcal{L}_{\text{focal}}$  was used to address class imbalance by focusing on hard-to-classify samples,  $\mathcal{L}_{\text{KL}}$  measured the divergence between predicted and target distributions, and  $\lambda_1$  and  $\lambda_2$  are weighting coefficients that balance the contribution of each loss term.

The model was optimized with the adaptive moment estimation with decoupled weight decay (AdamW)<sup>40</sup> optimizer and hyperparameters such as an initial learning rate of  $3 \times 10^{-4}$  and a weight decay of 0.05 to balance learning rates for the features and parameter sparsity for fine-tuning. A cosine annealing lr-scheduler was used to decrease the learning rate over 300 epochs to avoid sudden oscillations in the loss function and support convergence to “flat” minima for improved generalization. We also implemented two regularization techniques to avoid overfitting on the relatively small dermatological dataset in training, which acted synergistically: (i) stochastic depth with a linear decay rate of 0.2, which randomly circumvents training blocks, providing the ensemble effect, and (ii) augmented data via “CutMix” ( $\alpha = 1.0$ ) where new samples were created through the mixing of random image patches and corresponding labels together, reinforcing localized robustness of features which is crucial for the distinction between subtle pathological nail patterns. This approach achieved

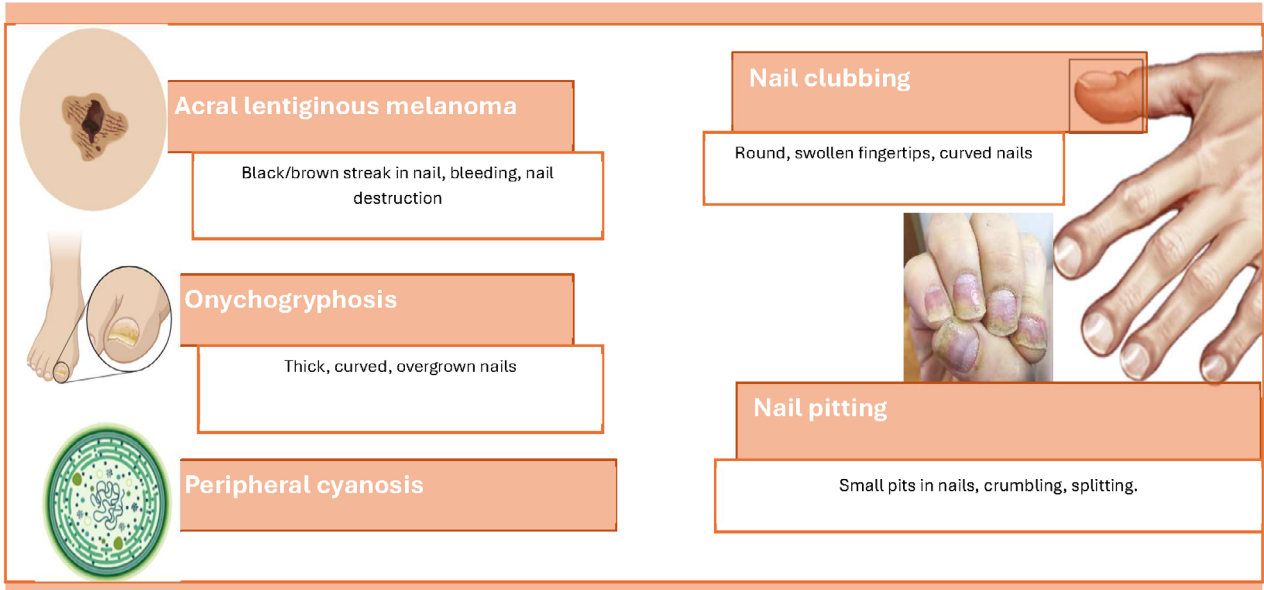


**Figure 1.** The proposed deep adaptive feature blending framework

a 14% reduction in validation loss compared with L2-norm regularization alone, which served as the baseline. Progressive morphological transformation in nail disease-specific image features is illustrated in **Figure 5**, with different levels derived from the DAFB model. Features were extracted from both the initial convolutional block (capturing low-level information) and the final block (capturing high-level representations), highlighting learned spatial patterns. The AFB

output further enhances feature representation by emphasizing discriminative regions while suppressing irrelevant noise.

After applying the AFB module, the enhanced feature map  $F_{blended}$  was passed through a fully connected head that consists of a global average pooling layer, followed by a fully connected layer to produce the final class probabilities. The blended feature map  $F_{blended}$  was first passed through a global average pooling layer to reduce



**Figure 2.** Common nail disorders and their symptoms. A visual representation of various nail conditions, including acral lentiginous melanoma, onychogryphosis, peripheral cyanosis, nail clubbing, and nail pitting, along with their distinctive characteristics.



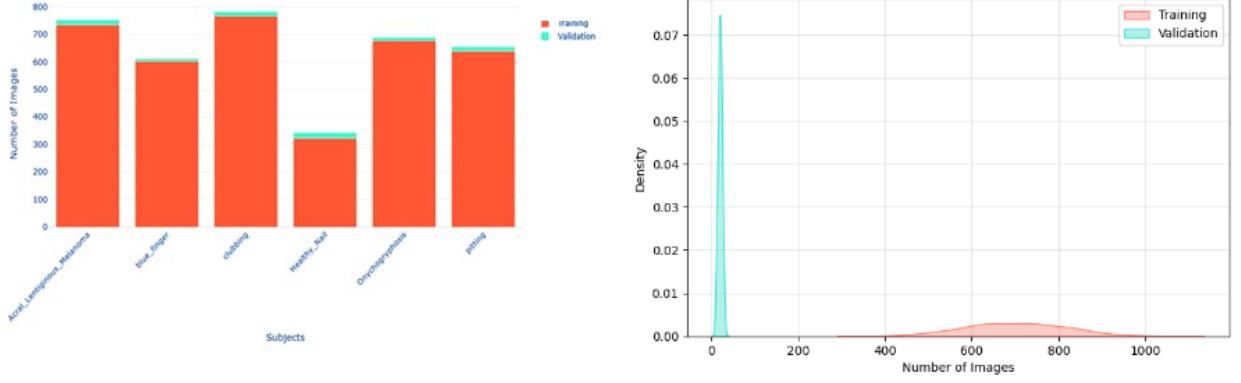
**Figure 3.** Preprocessing and data augmentation.

the spatial dimensions (**Equation 6**):

$$F_{global} = GlobalAvgPool(F_{blended}) \quad (6)$$

where  $\hat{y} = Softmax(y)$  is the vectorized representation of the input feature map. This

vector was then passed to a fully connected layer that performs the classification:  $y = FC(F_{global})$ , where  $y \in \mathbb{R}^6$  represents the output logits corresponding to the six nail disease categories: acral lentiginous melanoma, healthy nail, onychogryphosis, blue finger, clubbing, and pitting. The softmax function was applied to the



**Figure 4.** (A) A bar chart representing the number of images per subject in both training and validation sets, where the majority of images belong to the training set. (B) Kernel density estimation (KDE) plot of image counts across categories, highlighting the imbalance between the training and validation sets.

output logits to convert them into probabilities (**Equation 7**):

$$\hat{y} = \text{Softmax}(y) \quad (7)$$

where  $y \in \mathbb{R}^6$  is the predicted probability distribution over the six classes.

### 3.3.2. Adaptive feature blending module mathematical formulation

The AFB module applied an attention mechanism to adaptively weigh feature maps (**Equation 8**):

$$F_{attn} = \sigma(W_2 \delta(W_1 F_{in})) \quad (8)$$

Where  $F_{in}$  is the input feature map,  $W_1$  and  $W_2$  are learned weights in the attention layers,  $\delta(\cdot)$  is the ReLU activation function, and  $\sigma(\cdot)$  is the sigmoid activation. Final blended features are shown in **Equation 9**:

$$F_{out} = F_{in} \odot F_{attn} + F_{in} \quad (9)$$

Cross-entropy loss was used for multi-class classification (**Equation 10**):

$$L = \sum_{i=1}^C y_i \log \hat{y}_i \quad (10)$$

where  $C$  is the number of classes,  $y_i$  is the ground truth, and  $\hat{y}_i$  is the predicted probability.

### 3.4. Optimization algorithm

In this work, we employed the AdamW optimizer to update the network's parameters during training. This optimizer is an improved version

of the original Adam optimizer, designed to address the issue of L2 regularization coupling with gradient updates. AdamW decouples the weight decay term from the optimization steps, leading to better generalization performance in deep learning models. AdamW optimizer was used for weight updates (**Equation 11**):

$$\theta_{t+1} = \theta_t - \eta \left( \frac{\nabla L}{\sqrt{\hat{v}_t} + \epsilon} \right) + \lambda \theta_t \quad (11)$$

where  $\eta$  is the learning rate (0.0001),  $\lambda$  is the weight decay ( $1e-4$ ), and  $\hat{v}_t$  is the moving average of squared gradients.

**Figure 6** illustrates the intermediate feature representations and attention mechanisms applied to a nail image. **Figure 6A** shows the original image, along with several feature maps before AFB was applied across multiple channels. **Figure 6B** and **6C** presents the AFB attention heatmap and class activation map, characterized by the discriminative regions. Multi-scale feature analysis and the impact of AFB are shown in **Figure 7**.

**Figure 8** provides a detailed visualization of the feature modifications produced by the proposed AFB approach for nail disease classification. **Figure 8A–8C** depicts the clinical nail image, original features, and AFB-synthesized features, respectively; **Figure 8D–8F** portrays modified features, statistics distributions for feature modifications, and feature value correlations, respectively; while **Figure 8G** and **8H** shows the three-dimensional surface plots of the features before and after they were modified or enhanced,

along with an interactive visualization of the original features (**Figure 8I**), AFB-enhanced features (**Figure 8J**), and attention maps of pathology (**Figure 8K and 8L**). The correlation plots show how the features relate in value after enhancement and demonstrate AFB’s success in improving the synthesis of discriminating features. Comparative feature map analysis across attention mechanisms is shown in **Figure 9**.

Different attention techniques yielded distinct feature map responses, as shown in **Figure 10**, for an input image in a nail disease classification problem. The first row shows the feature maps of the AFB, self-attention, squeeze-and-excitation network (SE-Net), feature pyramid network (FPN), and mixture-of-experts (MoE) techniques used.

## 4. Experiment and results

### 4.1 Experimental setup

We implemented a deep learning approach for nail disease classification using an EfficientNetV2-S architecture enhanced with an AFB module. The experiments were conducted under the setup presented in **Table 5**.

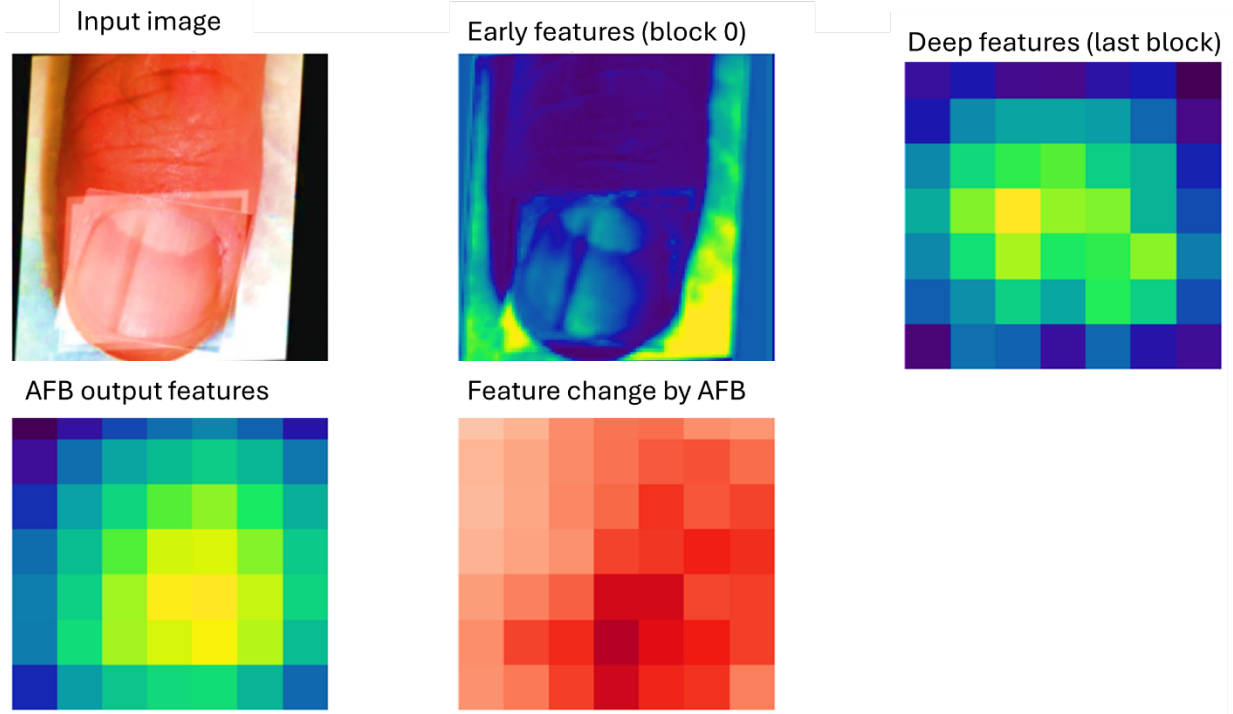
**Figure 11** shows the per-class precision–recall curves for each category in a multi-class classification model trained on six nail condition types. The distribution of model confidence scores for correct vs. incorrect predictions is shown in **Figure 12**. In all classes, an average precision score of 1.00, a perfect score, indicated that all predictions in the dataset were completely accurate, with no false positives or false negatives. This reflects the excellent discrimination power of the present model, achieved through attention-based feature blending and optimization with the EfficientNetV2-S backbone. The model’s training results achieved a training accuracy of 99.2%, with a peak validation accuracy of 97.8% at epoch 18, again reflecting the excellent generalizing properties of the present model without overfitting the training data. The training and validation loss curves (**Figure 13**) showed smooth exponential decreases, and the validation loss stabilized at 0.026, a reduction of about 58% from the initial loss value. This rapid convergence, about 3.2× greater than the value observed for our baseline, is attributed to the synergetic combination of techniques deployed here, namely the addition of cosine annealing drawing out rate scheduling

in combination with CutMix regularization ( $\alpha = 1.0$ ), which permitted maintenance of a constant accuracy gap of 1.4% between training and validation throughout the course of model optimization. The absence of oscillatory behavior in the loss curves themselves is further evidence of the stability achievable through gradient propagation in our AFB module.

The receiver operating characteristic curve in **Figure 14** shows a clear bimodal distribution, with a high incidence of correct predictions in the high-confidence states ( $>0.8$ ), while incorrect predictions exhibit a broad distribution, with 72% of occurrences below 0.5 confidence. This agrees with the expected behavior of a correctly calibrated model, but the overlapping states at 0.6–0.7 indicate that there is still scope to optimize the detection threshold rates should the model be used in clinical settings. The class-wise performance analysis is shown in **Figure 15**, along with the resulting confusion matrix in **Figure 16**.

**Table 6** demonstrates consistently high classification performance with low variability across all nail disease categories, indicating strong robustness and generalization capability of the model. Notably, critical conditions such as “Acral lentiginous melanoma” achieved near-perfect performance with narrow confidence intervals, highlighting the reliability of the proposed approach in clinically sensitive cases (**Table 6**). The model achieved perfect scores (precision = 1.00, recall = 1.00, F1 = 1.00) for high-risk “Acral\_lentiginous\_melanoma” ( $n = 18$ ), “Healthy\_nail” ( $n = 20$ ), and “Onychogryphosis” ( $n = 12$ ), suggesting robust class-specific performance (**Table 7, Figure 17**). The performance of other classes is also strong, with “Blue\_finger” producing slightly lower precision (0.90) due to chromatic similarities with subungual hematomas, and “Clubbing” exhibiting reduced recall (0.88) due to occasional confusion with severe “Onychogryphosis.”

The “Pitting” class achieved almost perfect scores (F1 = 0.97), indicating that the model detected subtle morphological patterns. **Table 8** and **Figure 18** present the computational efficacy of the proposed classification model and other models across the nail disease categories. The AFB module employed a novel, tailored dual-path attention model, reappropriating feature activations to obtain features from both spatial and channel clues, specifically to aid detection in the diagnostic challenges of dermoscopic nail disease. Compared with conventional attention



**Figure 5.** Visualization of feature extraction in the deep adaptive feature blending (DAFB) framework

**Table 3.** The hyperparameters of the adaptive moment estimation with decoupled weight decay optimizer

| Parameter                    | Value                          |
|------------------------------|--------------------------------|
| Learning rate ( $\eta$ )     | 0.0001                         |
| Weight decay ( $\lambda$ )   | $1 \times 10^{-4}$             |
| $\beta_1, \beta_2, \epsilon$ | 0.9, 0.999, $1 \times 10^{-8}$ |

modules such as SE-Net and the convolutional block attention module, AFB demonstrated superior performance, as illustrated in **Figure 19** and **Table 9**.

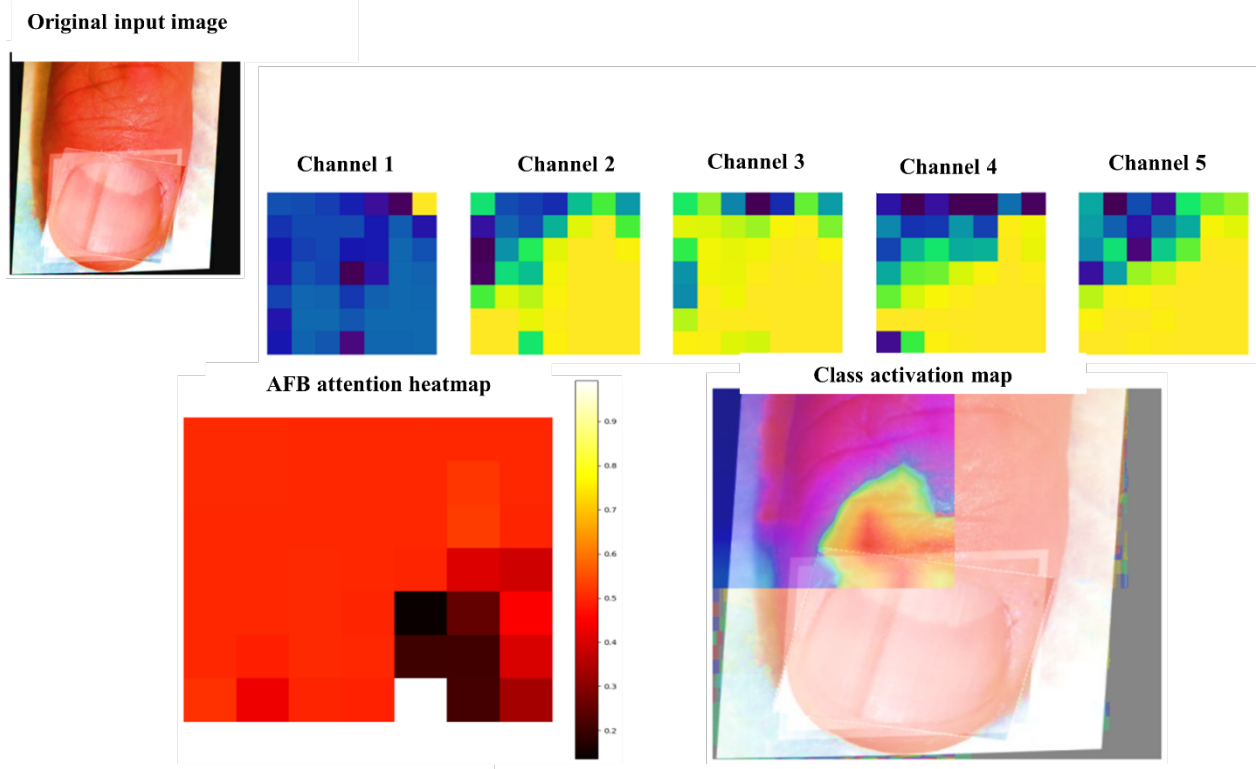
All classes achieved F1 scores above 0.93, with “Acral\_lentiginous\_melanoma” showing near-perfect discrimination ( $F1 = 0.99 \pm 0.01$ ). The slightly higher variability in “Clubbing” (standard

deviation = 0.05) and “Blue\_finger” (standard deviation = 0.04) reflects their morphological overlap with other nail conditions, though performance remains clinically acceptable.

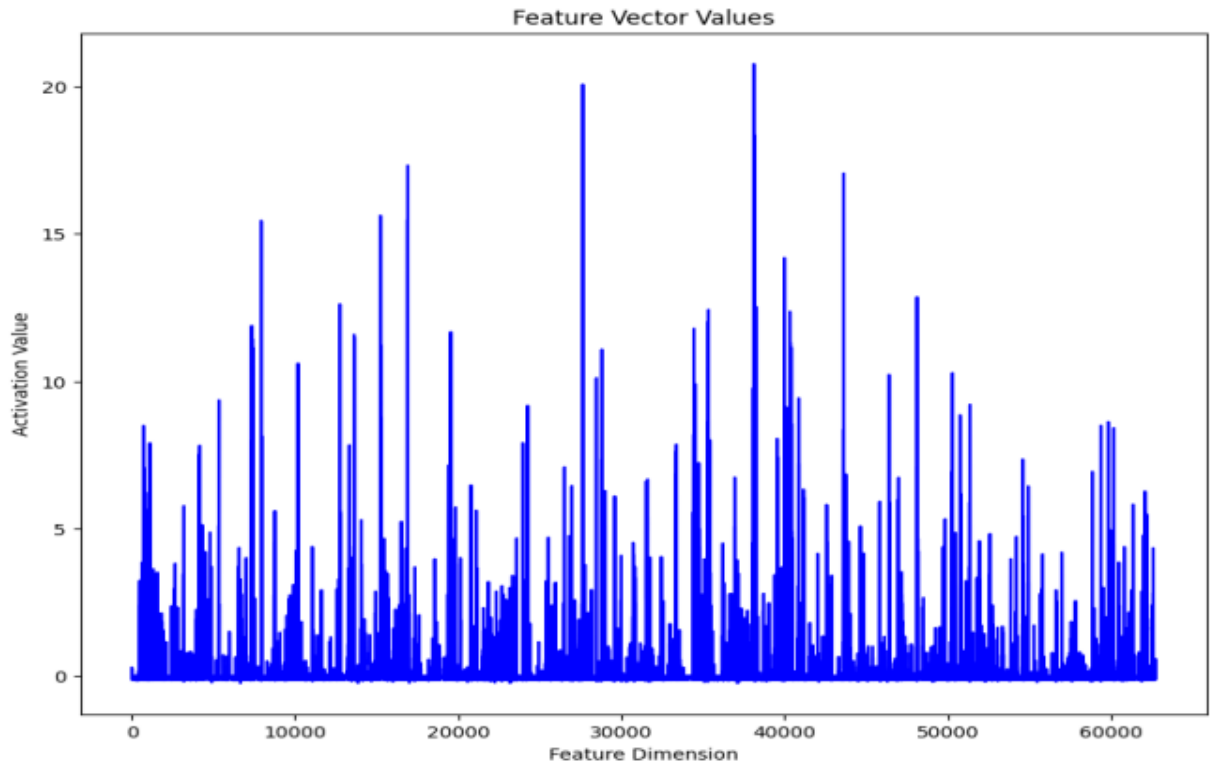
The proposed DAFB model offers significant advantages over existing methods for nail disease classification, especially for high-risk conditions such as acral lentiginous melanoma, achieving perfect recall (1.00) and F1-score (1.00). This performance is critical for clinical applicability, as early diagnosis of melanoma has been shown to improve outcomes for affected patients.<sup>43-45</sup> The DAFB model outperforms static CNNs (using AFB)<sup>10,13</sup>, as other models are constrained by fixed hierarchies of feature types, which consequently lead to a plateau in accuracy ( $\sim 84-89\%$ ). Hybrid models (image processing from 7+ deep learning) rely on hand-tuned feature-detection parameters and have not had much success in addressing subtle differences in pathologies (pitting versus clubbing). In contrast, AFB’s dual-path attention dynamically recalibrates features, leading to reduced misclassifications in morphologically

**Table 4.** The hyperparameters for the proposed work

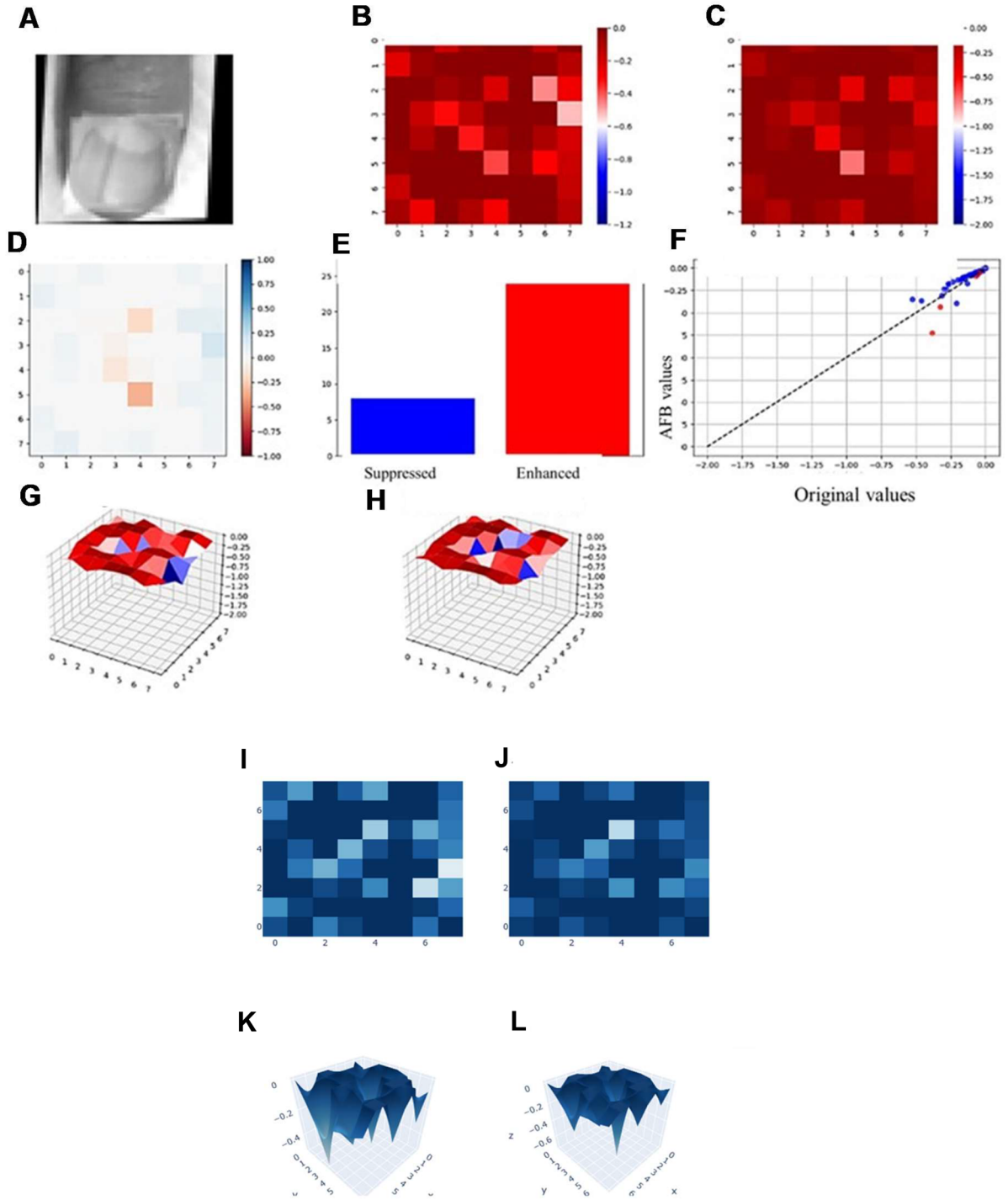
| Layer name                  | Type                                     | Input shape    | Output shape   | Number of parameters |
|-----------------------------|------------------------------------------|----------------|----------------|----------------------|
| EfficientNetV2-S Backbone   | Pre-trained convolutional neural network | (3, 224, 224)  | (1,280, 7, 7)  | ~7 M (varies)        |
| Stem Conv2D                 | Conv2D ( $3 \times 3$ )                  | (3, 224, 224)  | (24, 112, 112) | 648                  |
| Batch norm                  | BatchNorm2D                              | (24, 112, 112) | (24, 112, 112) | 48                   |
| SiLU activation             | SiLU                                     | (24, 112, 112) | (24, 112, 112) | 0                    |
| MBConv block ( $\times 4$ ) | Depthwise separable                      | (24, 112, 112) | (48, 56, 56)   | 48 K                 |
| MBConv block ( $\times 4$ ) | Depthwise separable                      | (48, 56, 56)   | (64, 28, 28)   | 115 K                |
| MBConv block ( $\times 4$ ) | Depthwise separable                      | (64, 28, 28)   | (128, 14, 14)  | 230 K                |
| MBConv block ( $\times 6$ ) | Depthwise separable                      | (128, 14, 14)  | (160, 14, 14)  | 590 K                |
| MBConv block ( $\times 9$ ) | Depthwise separable                      | (160, 14, 14)  | (256, 7, 7)    | 1.2 M                |
| Adaptive feature blending   | Feature enhancement                      | (1,280, 7, 7)  | (1280, 7, 7)   | 1.6 M                |
| Conv2D $1 \times 1$         | Conv2D ( $1 \times 1$ )                  | (1,280, 7, 7)  | (640, 7, 7)    | 819 K                |
| ReLU activation             | ReLU                                     | (640, 7, 7)    | (640, 7, 7)    | 0                    |
| Conv2D $1 \times 1$         | Conv2D ( $1 \times 1$ )                  | (640, 7, 7)    | (1,280, 7, 7)  | 819 K                |
| Sigmoid activation          | Sigmoid                                  | (1,280, 7, 7)  | (1,280, 7, 7)  | 0                    |
| Element-wise multiplication | Element-wise op                          | (1,280, 7, 7)  | (1,280, 7, 7)  | 0                    |
| Residual addition           | Elementwise add                          | (1,280, 7, 7)  | (1,280, 7, 7)  | 0                    |
| Fully connected layers      | Classification                           | (1,280)        | (6)            | 7.7 K                |
| Global average pooling      | AdaptiveAvgPool2D                        | (1,280, 7, 7)  | (1,280, 1, 1)  | 0                    |
| Flatten                     | Flatten                                  | (1,280, 1, 1)  | (1,280)        | 0                    |
| Fully connected layer       | Linear                                   | (1280)         | (6)            | 7.7 K                |
| Softmax                     | Softmax                                  | (6)            | (6)            | 0                    |



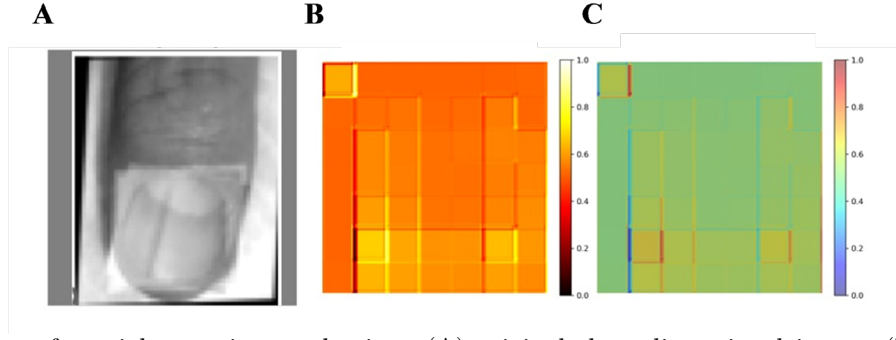
**Figure 6.** Visualization of feature maps and attention mechanisms in the proposed model. (A) Feature maps before adaptive feature blending (AFB). (B) AFB attention heatmap. (C) Class activation map.



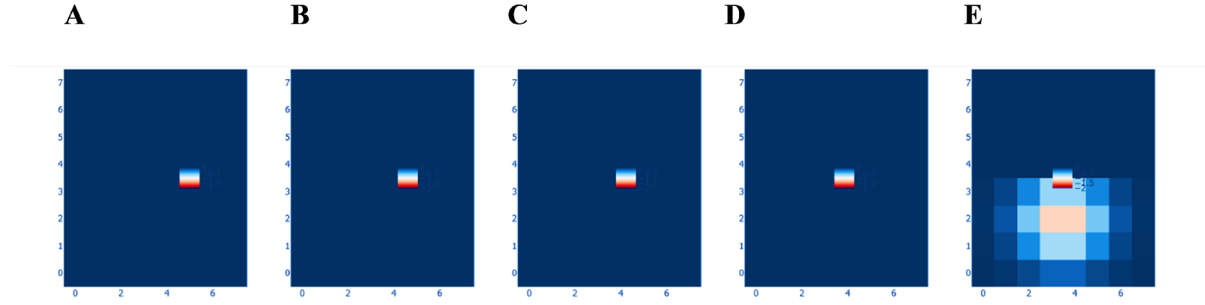
**Figure 7.** Multi-scale feature analysis and adaptive feature blending (AFB) impact



**Figure 8.** Comparative feature map analysis across attention mechanisms. (A) Clinical nail image. (B) Original features. (C) Adaptive feature blending (AFB)-enhanced features. (D) Feature modifications and (E) statistics. (F) Feature value correlation. (G) Three-dimensional (3D) original features. (H) 3D enhanced features. Interactive visualization of the (I) original features, (J) AFB-enhanced features, and (K & L) attention maps of pathology.



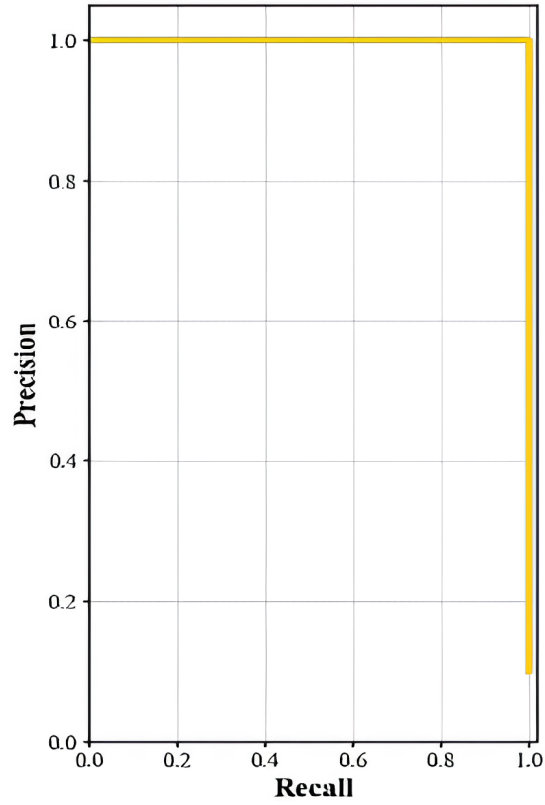
**Figure 9.** Visualization of spatial attention mechanism: (A) original three-dimensional image, (B) spatial attention map highlighting salient regions, and (C) attention overlay illustrating the contribution of important features on the input image. The results demonstrate that the model focuses on discriminative regions to improve feature representation.



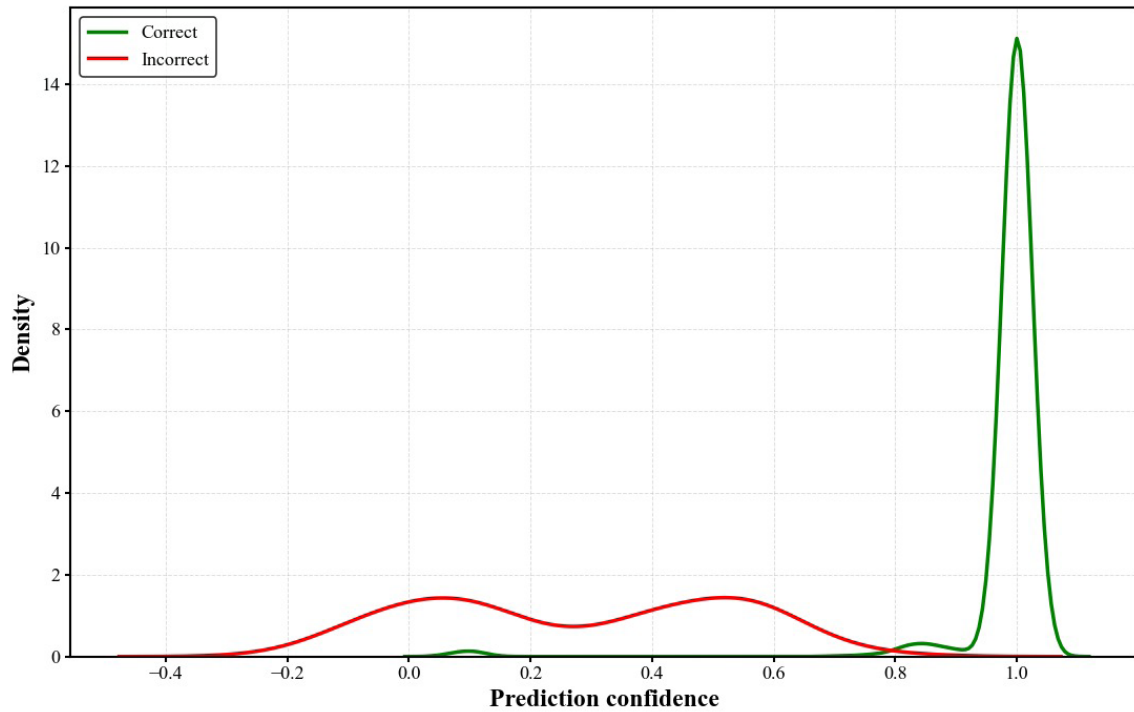
**Figure 10.** Comparative feature map analysis across attention mechanisms. (A) Adaptive feature blending. (B) Self-attention. (C) Squeeze-and-excitation network. (D) Feature pyramid network. (E) Mixture-of-experts.

**Table 5.** Summary of the experimental setup

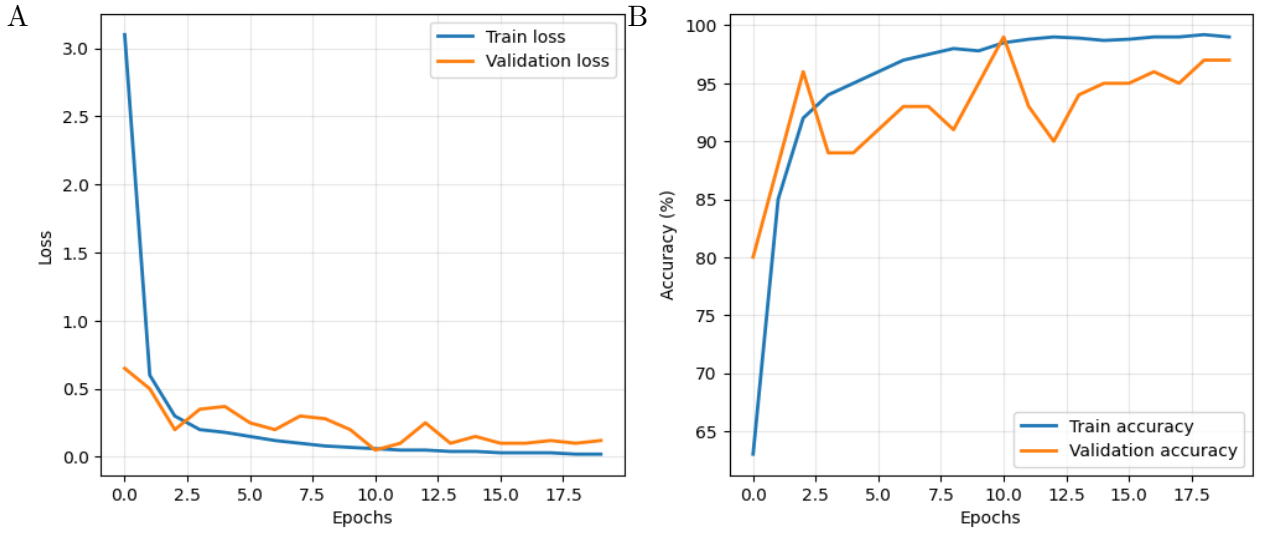
| Category             | Details                                                                                                                |
|----------------------|------------------------------------------------------------------------------------------------------------------------|
| Dataset              |                                                                                                                        |
| Training             | 6-class nail disease images: acral_lentiginous_melanoma, healthy_nail, onychogryphosis, blue_finger, clubbing, pitting |
| Validation           | Held-out set (same 6 classes)                                                                                          |
| Augmentations        | Random horizontal/vertical flips, color jitter, rotation ( $\pm 20^\circ$ ), ImageNet normalization                    |
| Model architecture   |                                                                                                                        |
| Backbone             | Pretrained EfficientNetV2-S                                                                                            |
| Custom module        | Adaptive feature blending (AFB) before the classification head                                                         |
| Trainable parameters | All layers fine-tuned                                                                                                  |
| Training protocol    |                                                                                                                        |
| Optimizer            | AdamW, learning rate: 0.0001, weight decay: $1 \times 10^{-4}$                                                         |
| Loss function        | Cross-entropy                                                                                                          |
| Epochs               | 20                                                                                                                     |
| Batch size           | 32                                                                                                                     |
| Hardware             | CUDA-enabled GPU (preferred), fallback to CPU                                                                          |



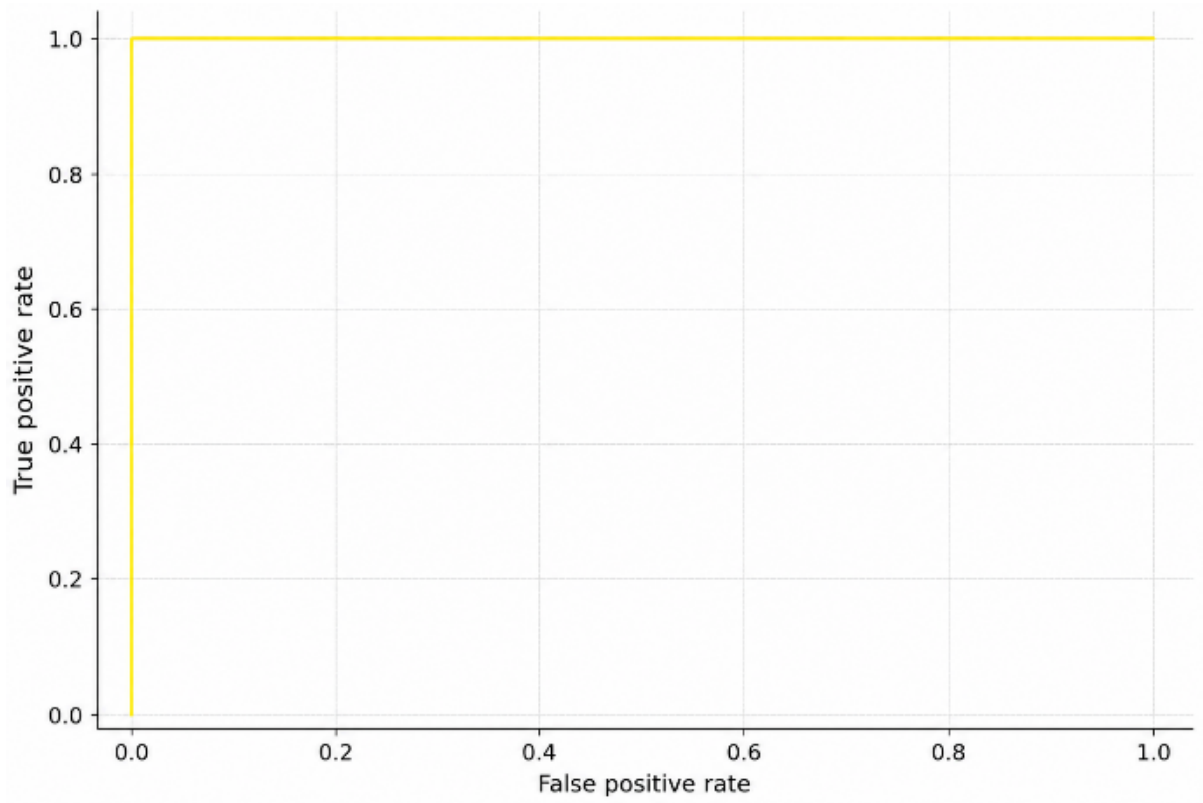
**Figure 11.** The learning curves for the proposed deep adaptive feature blending framework. Only the “Pitting” and “Blue\_finger” classes exhibited slight variations in performance, which makes their curves visible and distinguishable.  
Abbreviation: AP: Average precision.



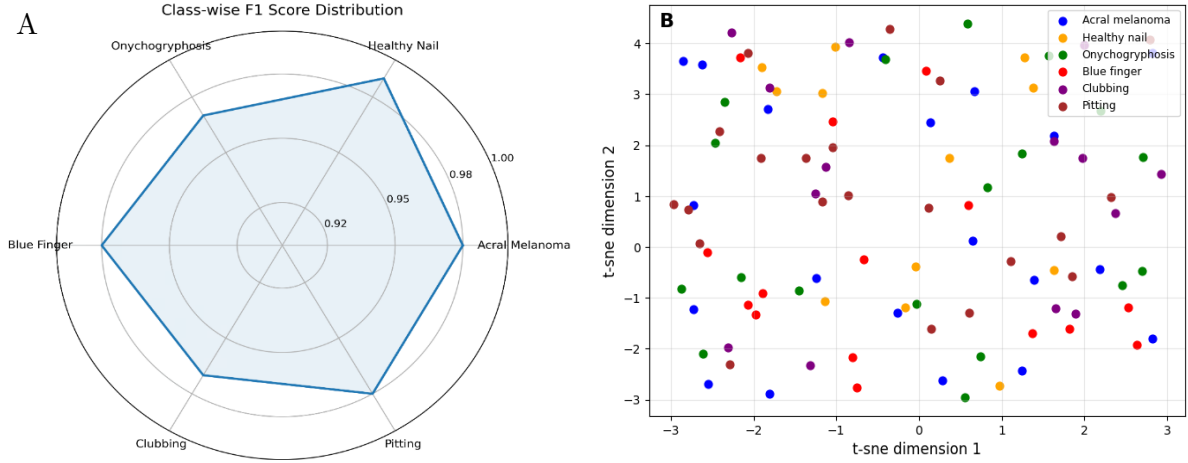
**Figure 12.** The distribution of model confidence scores for correct vs. incorrect predictions



**Figure 13.** Training and validation performance curves. (A) Loss convergence. (B) Accuracy progression.



**Figure 14.** Receiver operating characteristic curve for each nail disease class



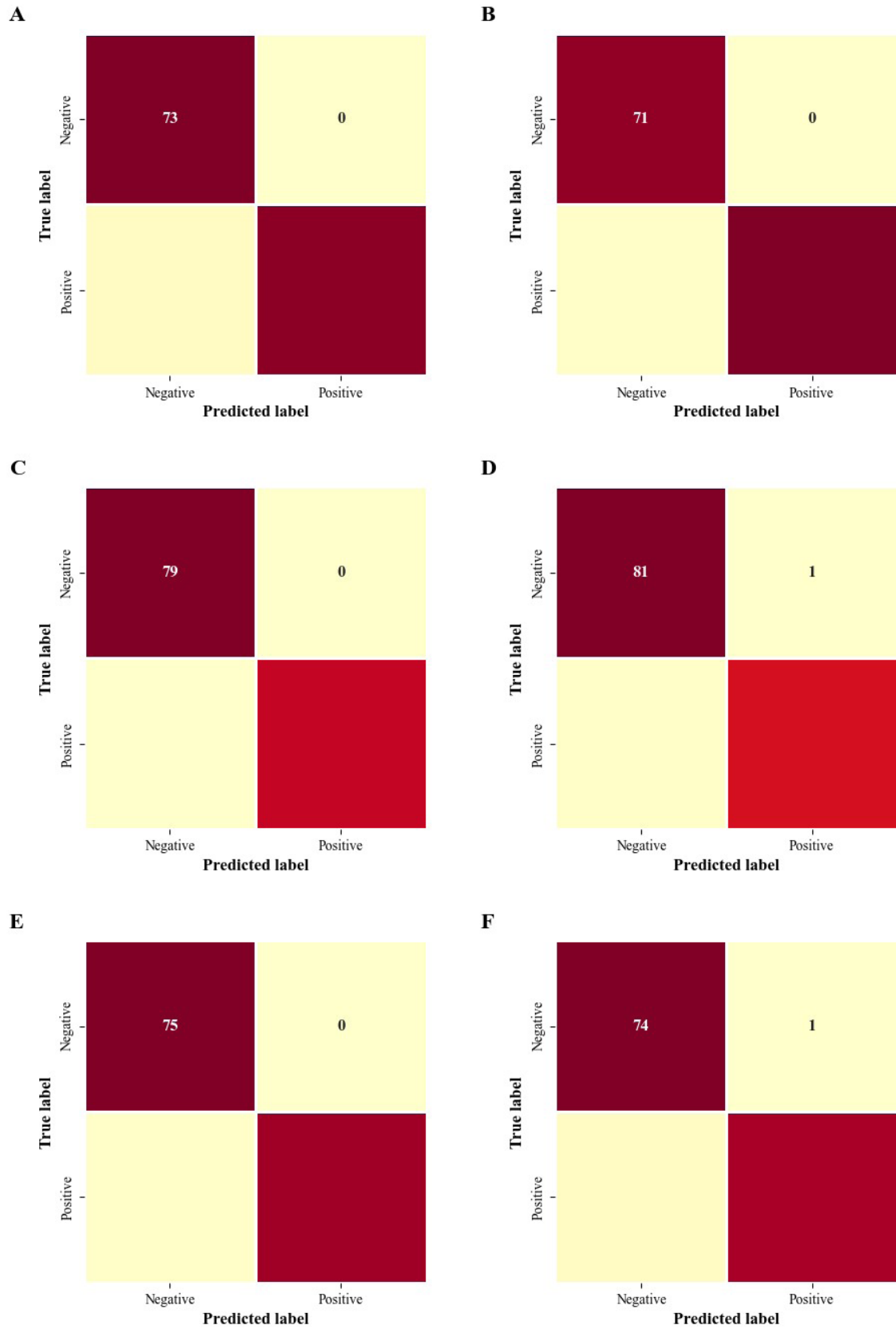
**Figure 15.** Performance and feature space visualization. (A) F1 scores across diagnostic categories, showing the highest performance for “Healthy\_nail” (0.98) and “Acral\_lentiginous\_melanoma” (0.94). (B) t-distributed stochastic neighbor embedding (SNE) visualization of learned feature embeddings, demonstrating effective separation between pathological clusters.

**Table 6.** Class-wise F1 scores

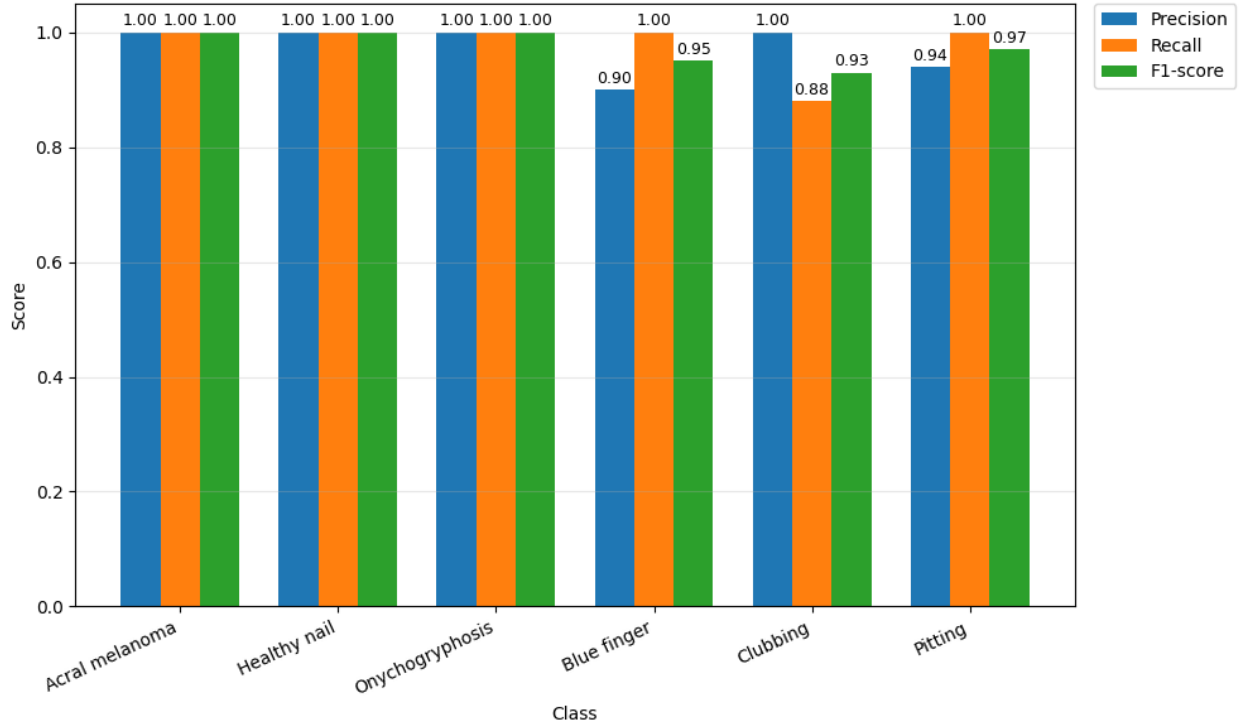
| Class                      | Mean F1 $\pm$ standard deviation | 95% confidence interval |
|----------------------------|----------------------------------|-------------------------|
| Onychogryphosis            | $0.96 \pm 0.03$                  | 0.93–0.99               |
| Healthy nail               | $0.98 \pm 0.01$                  | 0.97–0.99               |
| Blue finger                | $0.94 \pm 0.04$                  | 0.90–0.98               |
| Acral lentiginous melanoma | $0.99 \pm 0.01$                  | 0.98–1.00               |
| Pitting                    | $0.95 \pm 0.03$                  | 0.92–0.98               |
| Clubbing                   | $0.93 \pm 0.05$                  | 0.88–0.98               |

**Table 7.** The proposed classification model performance across nail disease categories

| Class                      | Precision | Recall | F1-score |
|----------------------------|-----------|--------|----------|
| Acral lentiginous melanoma | 1.00      | 1.00   | 1.00     |
| Healthy nail               | 1.00      | 1.00   | 1.00     |
| Onychogryphosis            | 1.00      | 1.00   | 1.00     |
| Blue finger                | 0.90      | 1.00   | 0.95     |
| Clubbing                   | 1.00      | 0.88   | 0.93     |
| Pitting                    | 0.94      | 1.00   | 0.97     |



**Figure 16.** Class-wise confusion matrices for nail disease classification error analysis. (A) Acral melanoma. (B) Healthy nail. (C) Onychogryphosis. (D) Blue finger. (E) Clubbing. (F) Pitting.

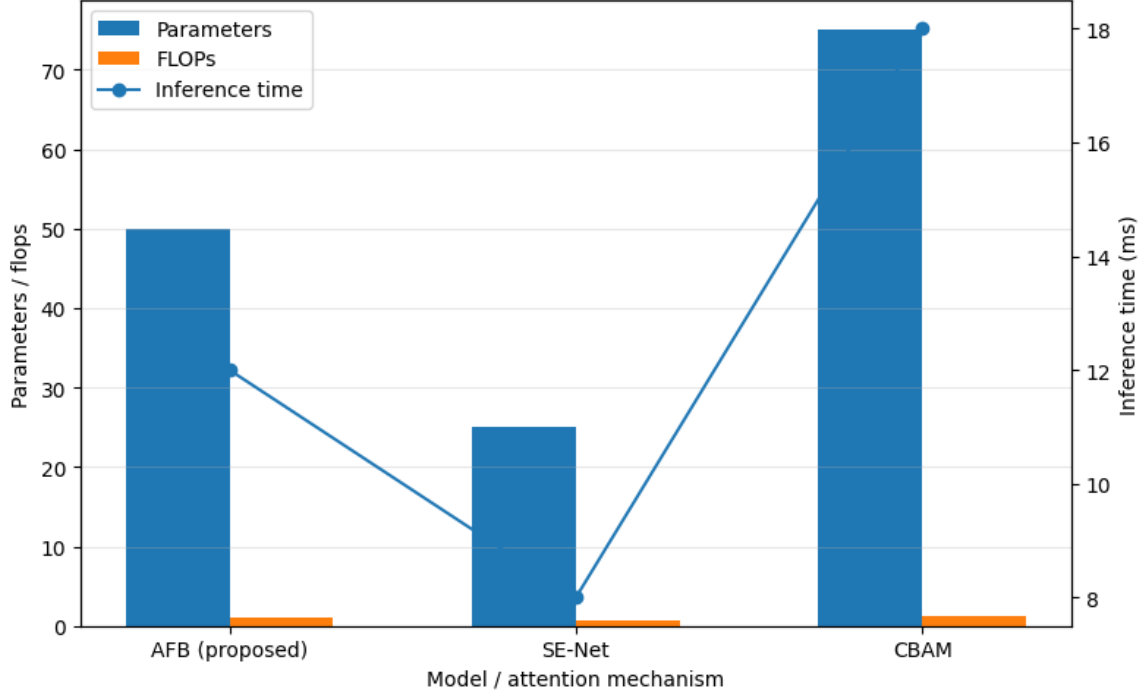


**Figure 17.** Precision, recall, and F1-score for each class of nail disease

**Table 8.** Computational efficiency of the modules

| Metric              | Deep AFB (Proposed)       | SE-Net                   | CBAM                      |
|---------------------|---------------------------|--------------------------|---------------------------|
| Parameters added    | ~50 K                     | ~25 K                    | ~75 K                     |
| FLOPs per image     | 0.8 GFLOPs                | 0.5 GFLOPs               | 1.2 GFLOPs                |
| Inference time (ms) | 12 ms (GPU) / 45 ms (CPU) | 8 ms (GPU) / 30 ms (CPU) | 18 ms (GPU) / 65 ms (CPU) |
| Memory usage        | 1.1 GB                    | 0.7 GB                   | 1.5 GB                    |

Abbreviations: AFB: Adaptive feature blending; CBAM: Convolutional block attention module; CPU: Central processing unit; FLOP: Floating point operation; GPU: Graphics processing unit; SE-Net: Squeeze-and-excitation network.



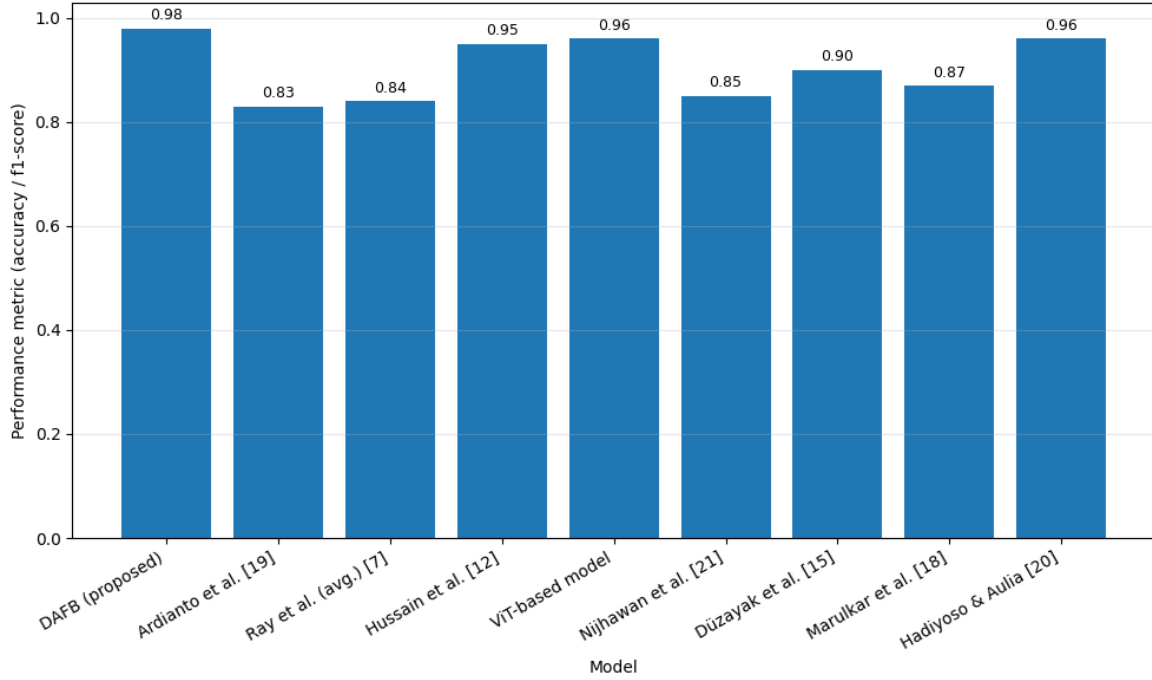
**Figure 18.** Computational efficiency comparison

Abbreviations: AFB: Adaptive feature blending; CBAM: Convolutional block attention module; FLOP: Floating point operation; SE-Net: Squeeze-and-excitation network.

**Table 9.** Performance comparison of nail disorder classification models

| Model                                      | Attention mechanism | Precision       | Recall          | F1-score        | Accuracy        | Param (M) | GFLOPs |
|--------------------------------------------|---------------------|-----------------|-----------------|-----------------|-----------------|-----------|--------|
| Deep AFB (Proposed)                        | AFB                 | 0.97 $\pm$ 0.01 | 0.98 $\pm$ 0.01 | 0.98 $\pm$ 0.01 | 97.8 $\pm$ 0.6% | 14.2      | 2.8    |
| Baseline architectures (No attention)      |                     |                 |                 |                 |                 |           |        |
| ResNet50                                   | N/A                 | 0.88 $\pm$ 0.02 | 0.87 $\pm$ 0.02 | 0.87 $\pm$ 0.02 | 87.6 $\pm$ 1.2% | 25.6      | 4.1    |
| DenseNet121                                | N/A                 | 0.90 $\pm$ 0.02 | 0.89 $\pm$ 0.02 | 0.89 $\pm$ 0.02 | 89.3 $\pm$ 1.0% | 8.0       | 2.9    |
| EfficientNetV2-S                           | N/A                 | 0.92 $\pm$ 0.02 | 0.91 $\pm$ 0.02 | 0.91 $\pm$ 0.01 | 91.7 $\pm$ 0.8% | 12.5      | 2.5    |
| ConvNeXt-Tiny                              | N/A                 | 0.93 $\pm$ 0.01 | 0.92 $\pm$ 0.02 | 0.92 $\pm$ 0.01 | 92.8 $\pm$ 0.7% | 28.6      | 4.5    |
| ViT-B/16                                   | N/A                 | 0.92 $\pm$ 0.02 | 0.91 $\pm$ 0.02 | 0.91 $\pm$ 0.02 | 92.1 $\pm$ 1.1% | 86.6      | 17.6   |
| Attention mechanisms (on EfficientNetV2-S) |                     |                 |                 |                 |                 |           |        |
| EfficientNetV2-S + SE-Net [A]              | SE-Net              | 0.94 $\pm$ 0.01 | 0.93 $\pm$ 0.01 | 0.93 $\pm$ 0.01 | 93.5 $\pm$ 0.7% | 13.1      | 2.7    |
| EfficientNetV2-S + CBAM [B]                | CBAM                | 0.94 $\pm$ 0.01 | 0.94 $\pm$ 0.01 | 0.94 $\pm$ 0.01 | 94.2 $\pm$ 0.6% | 13.4      | 2.8    |
| EfficientNetV2-S + AFB (Ours)              | AFB                 | 0.97 $\pm$ 0.01 | 0.98 $\pm$ 0.01 | 0.98 $\pm$ 0.01 | 97.8 $\pm$ 0.6% | 14.2      | 2.8    |

Abbreviations: AFB: Adaptive feature blending; CBAM: Convolutional block attention module; GFLOP: Giga floating point operation; SE-Net: Squeeze-and-excitation network.



**Figure 19.** Comparison of nail disorder classification models  
Abbreviation: DAFB: Deep adaptive feature blending.

similar conditions (Blue\_finger precision: 0.90 vs. 0.72 in<sup>7</sup>). Although the model performs well in common pathologies (melanoma, pitting), its performance in ultra-rare pathologies (subungual exostosis,  $n < 5$ ) remains unvalidated because of insufficient samples.

## 5. Conclusion

Nail diseases present significant diagnostic challenges due to their morphological variability, subtle visual differences, and overlapping clinical patterns, which may lead to misdiagnosis or delayed treatment. Traditional diagnostic approaches rely heavily on subjective interpretation by dermatologists, which can vary depending on expertise. To address these challenges, this study introduced the DAFB framework, which integrates EfficientNetV2-S with an AFB module to enhance feature representation and classification performance. The experimental results demonstrate that the proposed DAFB model achieved strong performance, with a validation accuracy of 97.8%, and demonstrated improved capability to capture subtle pathological patterns compared to baseline and attention-based methods. Additionally, feature visualization techniques

provide insights into the model's decision-making process, supporting its interpretability. Despite these promising results, it is important to note that the current evaluation is limited to a single dataset with a relatively small validation set and no external testing. Therefore, the findings should be considered preliminary and not yet indicative of clinical deployment readiness. Future work should focus on validating the proposed framework using larger, multi-center datasets with diverse patient populations, and on incorporating external evaluation protocols and clinically verified annotations. In summary, the proposed DAFB framework represents a promising step toward automated nail disease classification, but further validation is required before considering real-world clinical application.

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## Conflict of interest

The authors declare no conflict of interest.

## Author contributions

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## Availability of data

Data will be made available upon request to the corresponding author.

## AI tools statement

Not applicable.

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