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Enhanced Skin Lesion Detection Using Concatenated DenseNet and Multi-Attention Mechanisms

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***Abstract*—Skin lesions, which often signal underlying health issues, represent deviations from normal skin appearance. Skin diseases, including the potentially serious condition of skin cancer characterized by abnormal cell growth, encompass a spectrum of health concerns. The timely detection of lesions is paramount for diagnosis and cancer prevention, yet pinpointing affected areas accurately presents challenges due to the complexity and expense of diagnostic tests. This paper presented an innovative automated solution that leveraged transfer learning through the integration of DenseNet models, fine-tuned with three attention mechanisms, to efficiently extract salient features for lesion detection. This was achieved by iteratively concatenating the models. Initially, all DenseNet models underwent incorporation and fine-tuning with attention mechanisms, followed by concatenation to derive final features. This process was reiterated across all DenseNet variants, culminating in the creation of Concatenated DenseNet (CDN). Evaluation on the ISIC 2018 dataset revealed a notable accuracy of 97.08% for our proposed model. Additionally, Gradient Class Activation Map (GradCAM) was utilized to find out the specific region of interest during classification, which improved the explainability of the architecture. Our study not only enhanced accuracy but also advanced the utilization of transfer learning and various augmentation approaches. The insights from this research offered promising avenues for enhancing early detection of skin lesions, thereby contributing to the prevention of skin cancer.**

***Index Terms*—Skin Lesion Prediction, Concatenated DenseNet (CDN), Fine-tuned Transfer Learning, Augmentation.**

I. Introduction

Skin lesions are variations from the usual appearance of the skin that frequently indicate underlying health issues. Skin diseases encompass various issues affecting skin health, with some being benign and others potentially cancerous. In 2022, more than 1.5 million new cases of skin cancer were diagnosed worldwide, making it one of the most common types of cancer [1].

Detecting and treating melanoma early, before it spreads to the lymph nodes, leads to a survival rate of nearly 99% [2]. Early detection of skin lesions is crucial for diagnosis, yet high costs and complexity of tests often deter individuals. Automated systems leveraging artificial intelligence (AI), including machine learning (ML) and deep learning (DL), have the potential to streamline the diagnostic process, improving accessibility and reducing costs.

Despite advances ML and DL for skin lesion detection, challenges remain. Models may exhibit biased predictions, favoring classes with abundant data, while issues with transfer learning can hinder deployment in resource-limited settings. Additionally, insufficient fine-tuning can degrade model accuracy, while an overemphasis on feature extraction may hide important medical symptoms. Interpretability remains a challenge, with complex models lowering clinician trust. Misuse of test data and inconsistent evaluation metrics slow down the assessment process. Addressing these difficulties is essential for enhancing the accuracy, reliability, and ethical application of ML and DL in clinical settings.

Our approach in this study is focused on tackling these problems by addressing the primary research questions presented below, which are important for creating the groundwork for solid architecture.

RQ1: What measures can be implemented to overcome class imbalance issues and improve the reliability and fairness of model predictions?

RQ2: What approaches can be employed to integrate multiple pre-trained models to enhance the model's comprehensiveness and adaptability instead of relying on a single pre-trained model?

Our primary focus remained on the research questions stated before, and we concluded the study with the following contributions.

1) To address the imbalance in the data, we augmented it, ensuring unbiased modeling for all classes, regardless of sample size.
2) We have introduced Attention Mechanisms in our CNN architecture to prioritize important features and improved performance by concatenating multiple pre-trained models.
3) We have incorporated three Attention Modules such as, Soft Attention, Channel Attention and Squeeze-Excitation Attention into one single architecture to assemble triple advantages into one.

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The rest of the paper is organized as follows: a literature review is provided in Section II, followed by a dataset description in Section III and a detailed research methodology in Section IV. Experimental results are analyzed in Section V, followed by answers to research questions in Section VI. The discussion and extended comparison are presented in Section VII, with threats to validity discussed in Section VIII. Finally, conclusions are drawn in Section IX.

II. Literature Review

Many studies address image classification complexities, using deep learning techniques like CNNs for feature extraction [6-12]. Some employ segmentation methods [13-17], while others use GANs for data augmentation [18-19].

Milton [3] investigates deep learning models like PNASNet-5-Large, InceptionResNetV2, SENet154, and InceptionV4 for melanoma detection from dermoscopic images. However, the achieved validation accuracy of 76% falls below expectations. Mahbod et al. [4] explore skin lesion classification using transfer learning with pre-trained CNNs and analyze the effect of image size. Despite utilizing various architectures and a fusion approach, they achieved a balanced multi-class accuracy of 86.2% on the ISIC 2018 dataset, which cannot be considered a satisfactory performance. Sun et al. [5] present a skin lesion classification technique leveraging EfficientNet CNNs pre-trained on ImageNet, integrating patient metadata and augmentation details. Their method attains a balanced multiclass accuracy of 88.7% for a single model and 89.5% for an ensemble model. Gouda et al. [6] employ CNNs to detect malignant and benign skin tumors using ISIC 2018, achieving 83.2% accuracy after dataset preprocessing and image enhancement with ESRGAN. Lopez et al. [7] use VGGNet for skin lesion classification, emphasizing early melanoma detection. Their approach, employing transfer learning, achieves a sensitivity of 78.66% and a precision of 79.74% on the ISIC Archive dataset. Lai and Deng [8] propose a hybrid model, CNMP, for medical image classification, integrating deep features from a convolutional neural network with selected traditional features. Their approach achieves 90.1% and 90.2% accuracy on HIS2828 and ISIC2017 datasets, respectively.

Hassan et al. [9] use DermoExpert, combining lesion segmentation, augmentation, and a hybrid CNN, achieving high AUC scores on ISIC datasets. However, class balance remains a challenge on ISIC-2018 despite promising results. Al-masni et al. [10] integrate skin lesion boundary segmentation and classification using FrCN and CNN classifiers, respectively. They achieve 89.28% accuracy with ResNet-50 on ISIC 2018, but reliance on two-stage cascade networks requires data preparation for each stage, indicating potential for improvement with a single-stage convolutional network. Khouloud et al. [11] introduce W-net for skin lesion segmentation and Inception-ResNet for classification, achieving an accuracy of over 97% on ISIC and PH2 datasets. Hosny and Kassem [12] introduce RDCNN for skin lesion diagnosis, trained and tested on six skin cancer datasets, achieving an accuracy of 95.05% on the ISIC 2018 dataset.

Rashid et al. [13] propose using GANs to generate synthetic dermoscopic images for dataset augmentation, achieving an average F1-score of 0.834. However, concerns about GAN training instability, realism of medical images, and computational overhead arise. Qin et al. [14] propose a GAN-based data augmentation method for skin lesion classification, achieving high accuracy and performance metrics on ISIC 2018, with accuracy reaching 95.2%.

III. Dataset Description

Table I presents an overview of the "ISIC 2018" dataset, which serves as the primary dataset for this study, accessed from the ISIC Challenge repository [15]. It encompasses 10,015 dermatoscopic images, distributed across seven classes. Samples from each class are displayed in Fig. 1.

TABLE I: Frequency distribution of ISIC 2018 dataset.

No. of images	**Format**	**No of classes**	**Source**
10015	JPG	7	ISIC 2018

Class	**AK**	**BCC**	**BKL**	**DF**	**MEL**	**NV**	**VASC**
Samples	327	514	1099	115	1113	6705	142



(a) (b) (c) (d) (e) (f) (g)

Fig. 1: Sample images of different Classes (a) Actinic Keratosis (b) Basal Cell Carcinoma (c) Benign Keratosis (d) Dermatofibroma (e) Melanoma (f) Nevus (g) Vascular Lesions.

IV. Research Methodology

We start our procedure with data collection and preprocessing, then develop a novel CNN architecture with three attention modules: Squeeze and Excitation Attention (SEA), Soft Attention (SA), and Channel Attention (CA) which is incorporated with all versions of DenseNet (DN), i.e., DN121, DN169, and DN201. The model is trained and evaluated on validation data and tested on test data. Finally, we use GradCAM visualization to understand what the model is paying attention to when making predictions, as shown in Fig. 2.

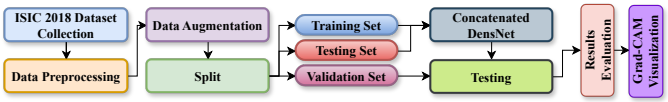


Fig. 2: Sequential workflow of research work.

A. Proposed Concatenated DenseNet Architecture

Fig. 3 illustrates the Concatenated DenseNet (CDN) architecture. First, the input passes through DN121, DN169, and DN201 pre-trained models. After tensor reshaping, three different attention mechanisms are used for each model, along with different convolutional blocks (CB) for fine tuning it.

The architecture is made up of six CB divided into three attention segments. Each CB includes four "Conv2D" layers with varying kernel sizes ($7\times7, 5\times5, 3\times3$, and 1×1) and four "BatchNormalization" layers. The output is then condensed using a 'MaxPooling2D' layer. The initial CB of each segment contains 128 filters, while the second has 256 filters. Each attention module is linked in a supportive manner. ReLU activation function is utilized in all convolutional layers to address the issue of vanishing gradients. The outputs of each segment are flattened and combined, and the features extracted from the three DenseNet architectures are concatenated again. Then, the final concatenated features are fed into fully connected layers of 256, 128, and 7 (representing the number of classes) neurons, respectively. Each dense layer includes dropout, with the first and second layers having dropout rates of 35% and 25%, respectively. Finally, the softmax activation function is used on the final layer for predicting class probabilities.

B. Attention Module

Attention modules within neural networks facilitate the prioritization of essential input features, disregarding less significant ones.

Channel Attention (CA): CA computes attention weights per channel using mean and standard deviation [16].

$$w_c = \sigma(W_2\delta(W_1 x)) \tag{1}$$

Where x = input feature maps of size $C \times H \times W$, W_1 and W_2 = weight matrices, δ = ReLU, σ = sigmoid, and w_c = calculated attention weights for each channel [17].

$$y_c = w_c \odot x \tag{2}$$

where $\odot$ denotes element-wise multiplication. This operation results in enhanced feature maps, denoted as y_c.

Squeeze and Excitation Attention (SEA): The SEA module involves squeezing to reduce spatial dimensions and excitation to learn channel-wise attention weights [18].

$$z = GlobalAveragePooling(x) \tag{3}$$

$$s = ReLU(W_2\sigma(W_1 z)) \tag{4}$$

$$y = s \odot x \tag{5}$$

Where x = input feature maps of size $C \times H \times W$, $W_1 \in \mathbb{R}^{\frac{C}{r}\times C}$ and $W_2 \in \mathbb{R}^{C\times\frac{C}{r}}$ = weight matrices, r = reduction ratio, and $\odot$ = element-wise multiplication.

Soft Attention (SA): SA determines the importance of individual input elements by assigning weights to focus on specific regions [19].

$$\alpha_i = \frac{exp(e_i)}{\sum_{j=1}^{T} exp(e_j)} \tag{6}$$

where α_i = weight assigned to i-th element, T = sequence length, and e_i = scalar score.

C. Justification of Our Proposed Architecture

Transfer learning with pre-trained CNN models leverages prior knowledge from large datasets, enabling faster convergence and better performance by capturing complex features. This is particularly advantageous for smaller datasets, reducing the need for vast computational resources and labeled data, though it may result in a heavier model [20].

Hyperparameter selection is key for optimal outcomes [21], hence, we manually tuned parameters. Batch normalization internal covariate shift, stabilizing layer input distributions for faster, more effective training.

Attention mechanisms help CNNs focus on key details, improving feature extraction. Channel attention strengthens important features, while Squeeze-and-Excitation Attention enhances performance with minimal overhead by refining channel dependencies. Soft attention offers flexible focus, aiding interpretability.

Concatenating several models harnesses the power of their diverse architectures. This integration can significantly improve prediction accuracy by creating a more well-rounded model capable of leveraging the strengths of each approach.

D. Performance Evaluation Measures

Various metrics, such as accuracy, precision, recall, f1-score, specificity, and ROC-AUC, are utilized to evaluate model effectiveness.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{8}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{9}$$

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{11}$$

E. Experimental Setup

Our architecture is run on Kaggle using GPU P100 and an Intel Xeon CPU. Lesion images of size (224, 224, 3) were partitioned: 15% for validation, 15% for testing, and the rest for training. We have trained our model for 270 epochs with batch size of 8, using Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy loss function.

V. Experimental Results Analysis

This section presents empirical and graphical results to assess classification performance, confirming the effectiveness of attention mechanisms and concatenation. Table II provides a comparison of our proposed CDN architecture with other approaches.

The CDN performs better than the individual pre-trained models with fine tuning (DN169, DN121, and DN201) in

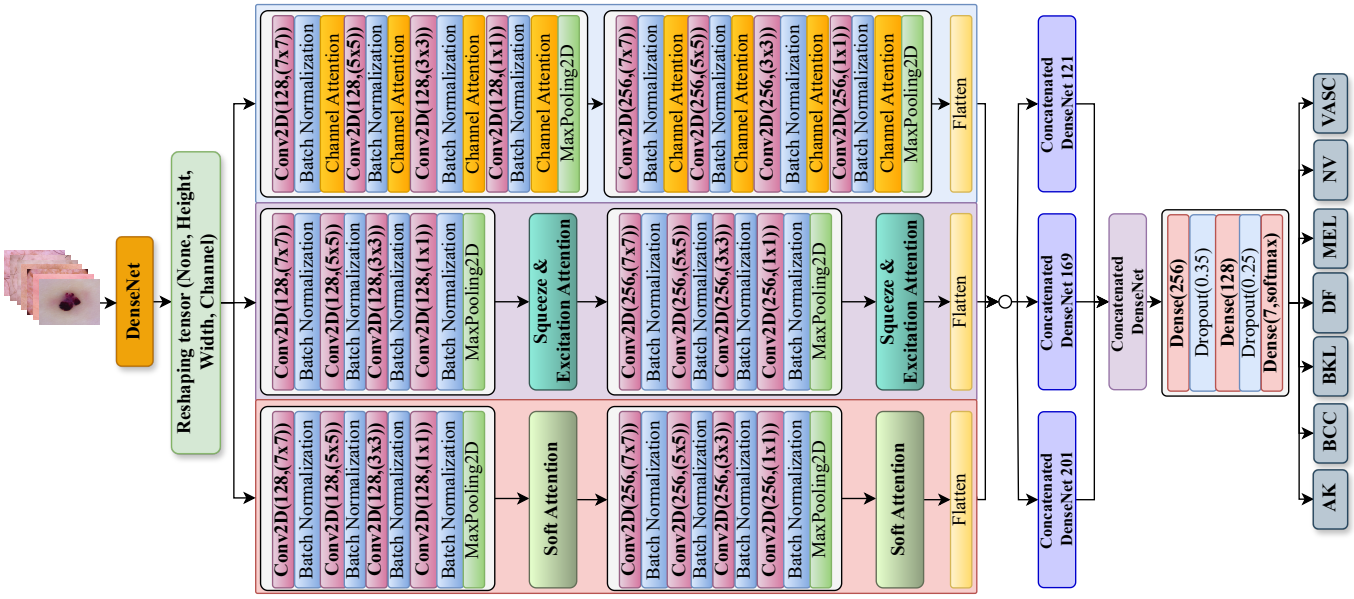


Fig. 3: Proposed Concatenated DenseNet architecture.

TABLE II: Comparative study of performance Metrics across various methods.

Evaluation Measures	CDN	DN169	DN121	DN201
Accuracy	**97.08**	96.27	95.36	96.08
Precision	**97.10**	96.27	95.38	96.08
Recall	**97.08**	96.27	95.36	96.08
F1-Score	**97.06**	96.26	95.36	96.07
Specificity	**99.50**	99.36	99.20	99.33

all evaluation measures. More specifically, CDN achieves an accuracy of 97.08%, higher than the individual models' accuracies of 96.27%, 95.36%, and 96.08% respectively. Other metrics also show CDN's superiority in improving model performance.

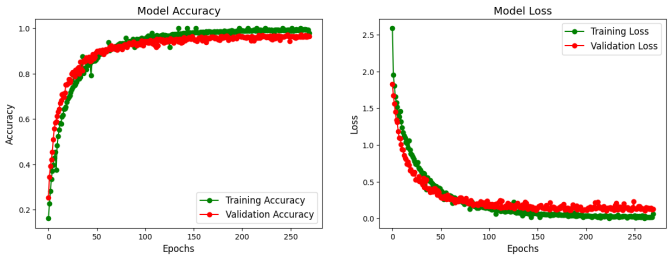


Fig. 4: Accuracy and Loss Curve of the Proposed Model.

The accuracy and loss curve for the proposed CDN architecture are displayed in Fig. 4.

Since the CDN achieved the highest accuracy in classifying the seven skin lesion states, its Confusion Matrix is shown in Fig. 5. This highlights the benefit of combining multiple models with attention mechanisms for better results compared to using a single model.

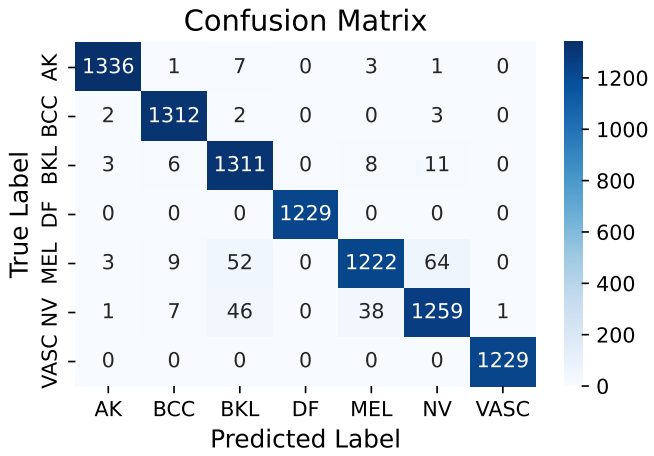


Fig. 5: Confusion Matrix obtained from proposed model.

Fig. 6 shows the ROC-AUC curve of our model, indicating that it doesn't favor the majority classes. Our model isn't overfitted to the training data and performs well in classifying skin lesions. This confirms its reliability and effectiveness for this task.

VI. Answers to the Research Questions

a) ***Answer of RQ1:*** Data augmentation balances class distribution for skin lesion classification training. By augmenting the dataset before partitioning it into testing, training, and validation sets, bias towards majority classes is prevented, ensuring each set contains a similar number of data. This makes it the most effective technique for addressing data imbalance.

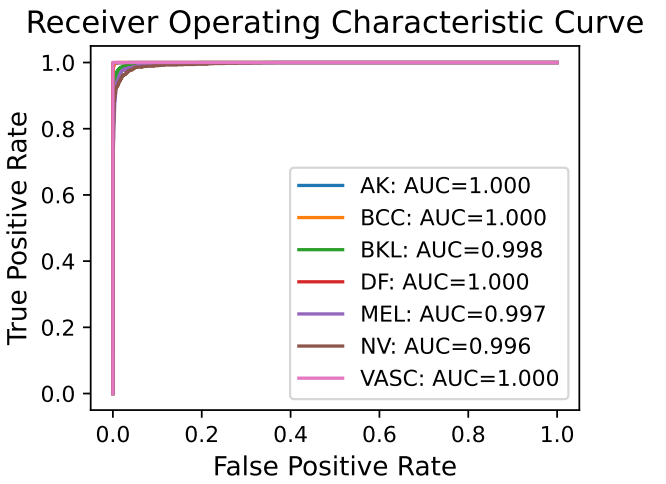


Fig. 6: ROC-AUC Curve.

*b) **Answer of RQ2**:* We enhanced our model's performance by combining three pre-trained models (DenseNet169, DenseNet121, and DenseNet201) without relying on just one. Each model used three attention mechanisms to extract various features effectively: Channel Attention (CA), Squeeze and Excitation Attention (SEA), and Soft Attention (SA). By combining the attention mechanisms for each model and then merging all three models together, we extracted the most significant features for improved performance.

VII. Discussion and Extended Comparison

Our model utilizes multiple attention mechanisms to classify skin lesions accurately. Since the explainablity is one of the most important contribution of any study [22], GradCAM heatmaps, like in Fig. 7, offer valuable insights by highlighting critical regions in images. Each pre-trained model, equipped with three attention mechanisms, emphasizes different areas, enhancing overall accuracy when combined. This approach outperforms individual models, demonstrating its effectiveness in lesion classification.

Beyond achieving high accuracy, the model empowers dermatologists with the benefit of transparency. By understanding how the model arrives at its predictions through attention-based heatmaps, dermatologists can build trust in its decisions. This newfound trust, coupled with the ability to visualize the model's focus areas, can potentially enhance both diagnosis and treatment planning. The heatmaps essentially highlight crucial image features for human analysis, allowing dermatologists to leverage the model's insights alongside their own expertise. This synergistic approach between human and machine intelligence holds immense promise for the future of skin cancer detection.

The superiority of our proposed CDN architecture is further substantiated through comparison with existing literature, as outlined in Table III.

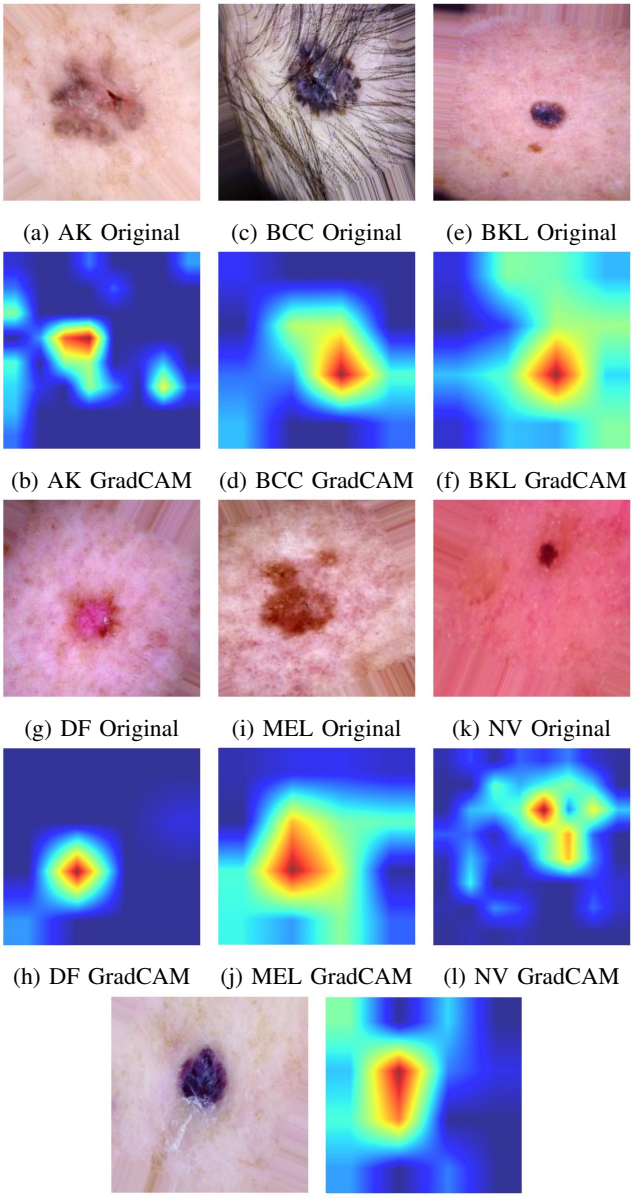


Fig. 7: Sample images of ISIC-2018 dataset classes with corresponding GradCAM Visualizations.

TABLE III: Comparison of our proposed model with other existing models.

Article	Accuracy	Precision	Recall	F1-Score	Specificity
[3]	76.00	-	-	-	-
[4]	86.20	91.3	-	-	-
[5]	89.50	-	-	-	98.10
[6]	83.20	-	-	-	-
[7]	81.33	79.74	-	-	-
[8]	90.10	-	-	-	-
[9]	-	85.00	86.00	-	-
[10]	89.28	-	-	81.28	87.16
[11]	96.97	95.71	-	-	97.87
[12]	95.05	82.29	-	-	97.00
[13]	86.10	-	-	-	-
[14]	95.20	96.60	-	-	74.30
Ours	**97.08**	**97.10**	**97.08**	**97.06**	**99.50**

VIII. Threats to Validity

While our skin lesion diagnosis model achieved promising results using the ISIC 2018 dataset, its generalization to other datasets and clinical settings remains to be explored. To address this, we plan to incorporate additional datasets like ISIC 2017, ISIC 2019, and PAD-UFES-20 in future iterations. Furthermore, this study focused solely on image analysis, neglecting potentially valuable metadata associated with each lesion. In our future work, we aim to refine the model into a more lightweight version while simultaneously integrating these metadata features. This combined approach, along with the exploration of additional datasets, may improve the model's accuracy and broaden its applicability in real-world clinical settings. Finally, an ensemble approach can push the performance massively [23].

IX. Conclusion and Future Work

Detection of skin lesions is crucial for preventing the extreme growth of the death rate from skin cancer. However, the high cost and complexity associated with traditional diagnostic methods pose significant challenges. Leveraging artificial intelligence can revolutionize skin lesion classification by providing cost-effective and efficient solutions. Our study introduced an automated system that accurately identifies skin lesion statuses, aiding in cancer prevention. To enhance the accuracy of our multi-class classification approach, we explored various techniques. To address dataset imbalances, we employed data augmentation techniques. Using transfer learning and fine-tuning with three attention modules, we extracted features from DenseNet variants (DenseNet169, DenseNet121, and DenseNet201), combining their outputs for robust lesion detection. Moreover, we leveraged GradCAM visualization to understand our model's focus during disease classification. This not only improved interpretability but also highlighted key regions for early skin lesion detection, aiding dermatologists and potentially improving patient outcomes.

Looking ahead, our focus will shift towards refining this model into a more lightweight version and extending its applicability through exploration with additional datasets such as ISIC 2019, ISIC 2017, and PAD-UFES-20, with the ultimate aim of enhancing model generalization.

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