



A Hybrid Deep Learning Model Combining VGG19 and AD_Net through Feature-Level Fusion for Real-Time Skin Cancer Classification

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Abstract

Automated detection (AD) techniques are essential for early recognition of skin cancer. Hybrid models using feature fusion, which combine pre-trained CNNs with customized models, have shown superiority in real-time skin cancer pathology classification. This study combines VGG19 feature maps with a novel learning network based framework called AD_Net to enhance classification accuracy. VGG19 facilitated robust low-level feature extraction, while AD_Net brilliantly extracts specialized patterns. This strategy provided a flexible and fast architecture, suitable for real-time medical applications. This work led to the classification of three of the most lethal skin cancer types. The model was trained and validated using experiments on the publicly available ISIC2019 dataset. In order to improve the interpretability of the model's predictions, interpretable artificial intelligence (XAI) techniques particularly Grad-CAM were applied. Four baseline models EfficientNetB0, MobileNetV2, Inception-v3, and VGG16, were used to assess the proposal's efficacy. The suggested model outperformed the four baseline models with 99.18% accuracy, 99.0% precision, 99.0% recall, and 99.0% F1 score. Dermatologists and other medical professionals can use this method to detect skin cancer early.

Keywords: Hybrid models; Feature fusion; Skin cancer; Explainable AI (XAI); Automated diagnosis (AD_Net)

1. Introduction

Skin cancer is an abnormal growth of skin cells, often caused by overexposure to sunlight. It is one of the most common types of cancer. It is divided into three main types: basal cell carcinoma, squamous cell carcinoma, and melanoma (the most serious). Clinical evaluation begins when changes in the appearance of the skin are observed, and diagnosis is made through a skin examination and may be followed by a biopsy. Delayed diagnosis can lead to the spread of cancer cells to other parts of the body, reducing the chances of recovery. One of the main causes of its spread is exposure to ultraviolet radiation. Early detection and prompt treatment are key to preventing complications [1]. Potentially malignant skin tumors include melanoma (MEL), basal cell carcinoma (BCC), and squamous cell carcinoma (SCC) [2]. However, many cutaneous tumors show less aggressiveness than melanoma [3].

Recent years have seen great interest in skin cancer classification using artificial intelligence (AI). Researchers have made significant progress in this field, especially in recognizing disease patterns in medical images [4]. This has enhanced the clinical practice of dermatologists. Since skin diseases are complex in nature, specialists have a need for advanced techniques specifically designed to detect this condition [5]. Several hybrid approaches have

combined high-level features generated from expert consultations with low-level features obtained from deep learning tools to generate an optimized feature vector. This results in a more detailed analysis of the image [6]. For accurate analysis of medical images, we developed a hybrid model combining VGG19 and AD_Net specifically designed to visually detect melanoma from images. While minimizing biases due to dark skin or thick hair. The contributions of this study are as follows.

The proposed approach facilitates classification between different pathological conditions in endoscopic skin images.

- VGG19 enables accurate extraction of low-level features, while AD_Net can learn specialized patterns. This helped in the extraction of salient features that contributed to high classification accuracy.
- By using a feature fusion approach, complicated calculations are avoided. As a result, the model performs better.
- The class mismatch problems in ISIC 2019 were effectively resolved by using the data augmentation technique.
- By contrasting the evaluation metrics with the outcomes of four baseline classifiers EfficientNetB0, MobileNetV2, Inception-v3, and VGG16 the performance of the suggested model was assessed. The hybrid model performs better than the state of the art models, according to the results.
- The most crucial visual characteristics of the various forms of skin cancer were determined using the Grad-CAM heat map technique.

The structure of the paper is as follows: Section 2 provides a brief overview of the state-of-the-art hybrid methods for skin cancer detection. A brief summary of the ISIC 2019 skin cancer dataset and the underlying models are presented in Section 3. The AD_Net architecture used in this research is described in Section 4, along with the results and discussions that follow. Section 5 concludes.

2. Related Works

By combining deep learning with machine learning, the hybrid method has shown success in several fields. Feature-level fusion accelerates the disease diagnosis. There are some recent researches in machine learning and deep learning that address how to detect and classify skin cancer, which will be discussed in this section.

According to a paper by Keerthana 2023, this study developed a hybrid model for cancer diagnosis using DenseNet-20 classification, mobile network, and support vector machine. On the ISBI 2016 dataset, this model achieved an accuracy rate of 88.02% [7]. In 2023, Olayah developed a hybrid model for skin cancer detection that combines AlexNet, GoogLeNet, VGG16, and artificial neural network. To enhances performance [8].

Qian et al., proposed a method based on feature extraction using multiscale attention block aggregation and a class-specific weighting loss to address the data imbalance problem and improve model accuracy [9]. In another similar study, Abdelhafeez et al. (2023) presented a learning strategy using transformational learning to classify eight classes of lesions. They used a feature fusion approach, which resulted in improved accuracy [10]. Ogundokun et al. (2023), develops a hybrid network, using Xception and MobileNetV2 for skin disease detection [11].

In 2024, Naeem A and colleagues proposed a hybrid skin cancer detection method. Handcrafted (HC) and deep learning models, such as Inception V3 for feature extraction and CNNs for classification, are used. The use of handmade features and deep learning methods enhances classifier performance [12]. In Karthik's 2024 study, this research proposes a hybrid system that combines two approaches, group shuffle Depth-wise blocks (GSDW) and non-local attention blocks on one hand and a Swain transformer and dense set mixing non-local attention network on the other hand, which integrates DenseNet169, to improve performance. The proposed network achieves an accuracy of 94.21%, on the HAM10000 dataset [13].

Matin et al. (2024) used a hybrid approach to learning Vision Transformer and Inception-ResNet-v2 to balance accuracy and performance [14]. Kasim et al. propose a method for accurately classifying skin tumors. Employing pre-trained GoogleNet model for learning transfer [15]. Ullah et al. (2025) developed a hybrid architecture combining Radial Basis Function and deep convolution neural networks for improved classification accuracy [16]. A summary of hybrid deep learning studies is provided in Table 1.

Table 1: Comparative summary of hybrid deep learning research for skin cancer classification.

Research	Hybrid component	Datasets	Accuracy	Quantitative Assessments
Kirthana et al. (2023)	DenseNet201 + MobileNet + SVM	ISBI 2016	88.02%	SVM used for final classification
Olayah et al. (2023)	AlexNet + GoogLeNet + VGG16 + ANN	ISIC 2019	96.10%	Fusion of multiple deep networks
Qian et al. (2022)	CNN + Multiscale Attention Blocks	Ham10000	91.60%	Shape enhancement techniques used
Abdelhafeez et al.(2023)	Neutrosophic Clustering + Layer Fusion (GoogleNet, DarkNet)	ISIC 2019	84.5%	Feature fusion boosts accuracy
Ogundokun et al. (2023).	Xception + MobileNetV2	ISIC 2019	97.56%	100% sensitivity, 96.55% F1-score
Naeem A, et al. (2024)	handcrafted feature extraction (HC) methods and Inception V3	ISIC 2019	97.81%	Improvement of the classifier performance
Mateen et al. (2024)	U-Net + Inception-ResNet-v2 + Vision Transformer	ISIC 2020	98.65%	99.20% sensitivity, top performance
Kasim et al. (2020)	GoogleNet + Transfer Learning	ISIC 2019	94.92%	97% specificity, good generalization
Ullah et al. (2025)	CNN(Resnet50)+RBF CNN(VGG16)+RBF	ISIC2018,ISIC2017	83.02%, 72.15%	More interpretable hybrid mode

To address these issues, we designed a hybrid system that merging VGG19 with AD_Net, leveraging fine tuning techniques and merging the output features of both models to improve performance and robustness. By combining the efficiency of VGG19 feature extraction with the ability of our developed system to handle multi-scale features, we aim to achieve a better balance between speed and accuracy.

3. Baseline Models

Research demonstrates the effectiveness of transformative learning using pre-trained convolutional neural networks (CNNs), which are particularly useful in medical imaging datasets because their extended networks accommodate task-specific features. In our study, we selected a particular set of models with a conscious restriction on the number of layers. The quantity of layers is meticulously evaluated. The MobileNetV2 architecture is both efficient and rapid, particularly in resource-limited settings. This architecture is designed for mobile and embedded vision applications due to its capacity to capture intricate features [17]. EfficientNetB0 is a deep neural network designed for real-time applications that need performance and efficiency. It has been widely used in medical image datasets due to its high classification accuracy with few parameters, making it an ideal choice for dermatology classification.

On the other hand, we used VGG16, a trained network that can flexibly adapt to the requirements of medical image classification for feature extraction in transformative learning, although its performance is slower than that of newer architectures due to the large number of parameters [17].

We also used Inception-v3, a convolutional neural network with a wide depth and width of layers, which has been widely used in object recognition tasks due to its ability to balance classification accuracy with computational efficiency [18]. These networks were retrained on the dataset used in this study and identical pre-processing, boosting, and training protocols were applied in all models to ensure a fair and valid comparison. Including resizing all images to maintain compatibility with special input requirements, data augmentation techniques to enhance generalization. In addition, all models were trained with the same number of loops (e.g., 30) employing the ADAM optimizer with a constant learning rate of 0.0003, batch size = 16, and loss function (categorical cross-entropy). This standardized setup ensures that differences in performance arise from architectural differences and not from inconsistencies in preprocessing or training conditions.

3.1 Dataset Description (ISIC 2019 Skin Cancer Dataset)

In our approach, we used an available dataset obtained from ISIC 2019. For skin cancer images. These images total 25,331 images. These images represent eight different types of skin cancer, including actinic keratosis (AK), basal cell carcinoma (BCC), squamous cell carcinoma (SCC), benign keratosis (BK), dermatofibroma (DF), melanoma (MN), melanoma (MEL), and vascular lesion (VAS). All are in JPEG format. They were compiled from the MSK dataset, the HAM10000 dataset, and the BCN_20000 dataset [19]. In this study, 2233 images were used for basal cell carcinoma, 2243 images for basal cell carcinoma, and 2240 images for squamous cell carcinoma, the reason for using these three types is because they are considered the most deadly on humans and sometimes fatal according to reported medical statistics. Figure 1 shows a sample of the most common skin cancer images. According to the dataset guidelines, secondary use does not require additional ethical approval.

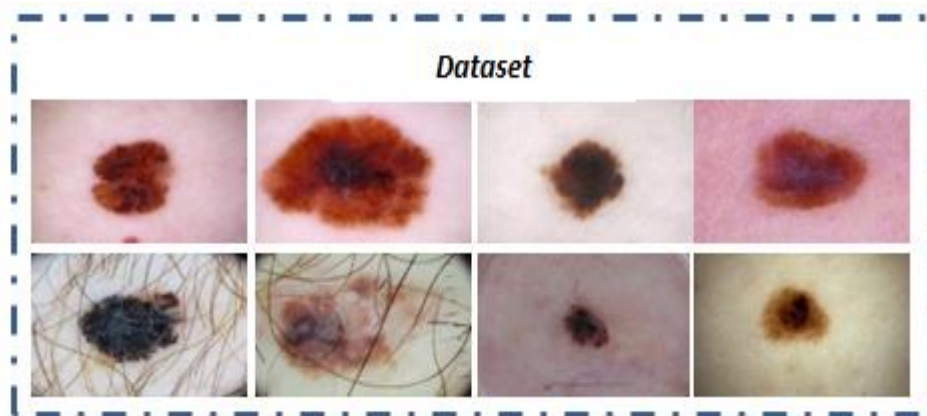


Figure 1. Skin cancer images from ISIC 2019 [19].

4. Proposed Methodology

This section discusses the suggested hybrid technique for categorizing skin images into three classifications. While only 3 out of 8 classes were used, this targeted approach minimizes noise from less important classes and allows for an in-depth analysis of the most dangerous cancers. To reduce the risk of overfitting resulting from using only three classes, effective techniques were adopted, including dropout, data augmentation, and batch normalization, which helped improve the model's generalization and reduce its reliance on recurring patterns. Figure 2 illustrates the complete process of the proposed method. Following parts explain various methodologies used in the classification of skin photos, as illustrated in Figure 2.

4.1 Pre-processing

To ensure compatibility with our approach and the pre-trained network, all photos were scaled to 224 x 224 pixels before being added to the model. We then normalized the image's pixels to 0–1. This stabilizes training. A 0.2 shift value arbitrarily shifts images horizontally and vertically. Doing so increases the dataset's diversity and creates a model that can handle modest changes. The approach's ability to handle varying sizes and accuracy and generalization with fresh photos are improved by random zooming by up to 20% when zoom scale = 0.2. The model can detect features regardless of their left-to-right position by reproducing the dataset with reversed copies and randomly flipping the images along the horizontal axis with the horizon flip parameter of True. We use the Rotate range=10 parameters rotate images randomly up to 10 degrees. This feature improves the model's flexibility and accuracy to new images and dataset alignment variation. While cropping parts of the image by 20%

results in random horizontal or vertical changes in the image's shape, this makes the model more general and better able to adapt to new images and focus on their content accurately.

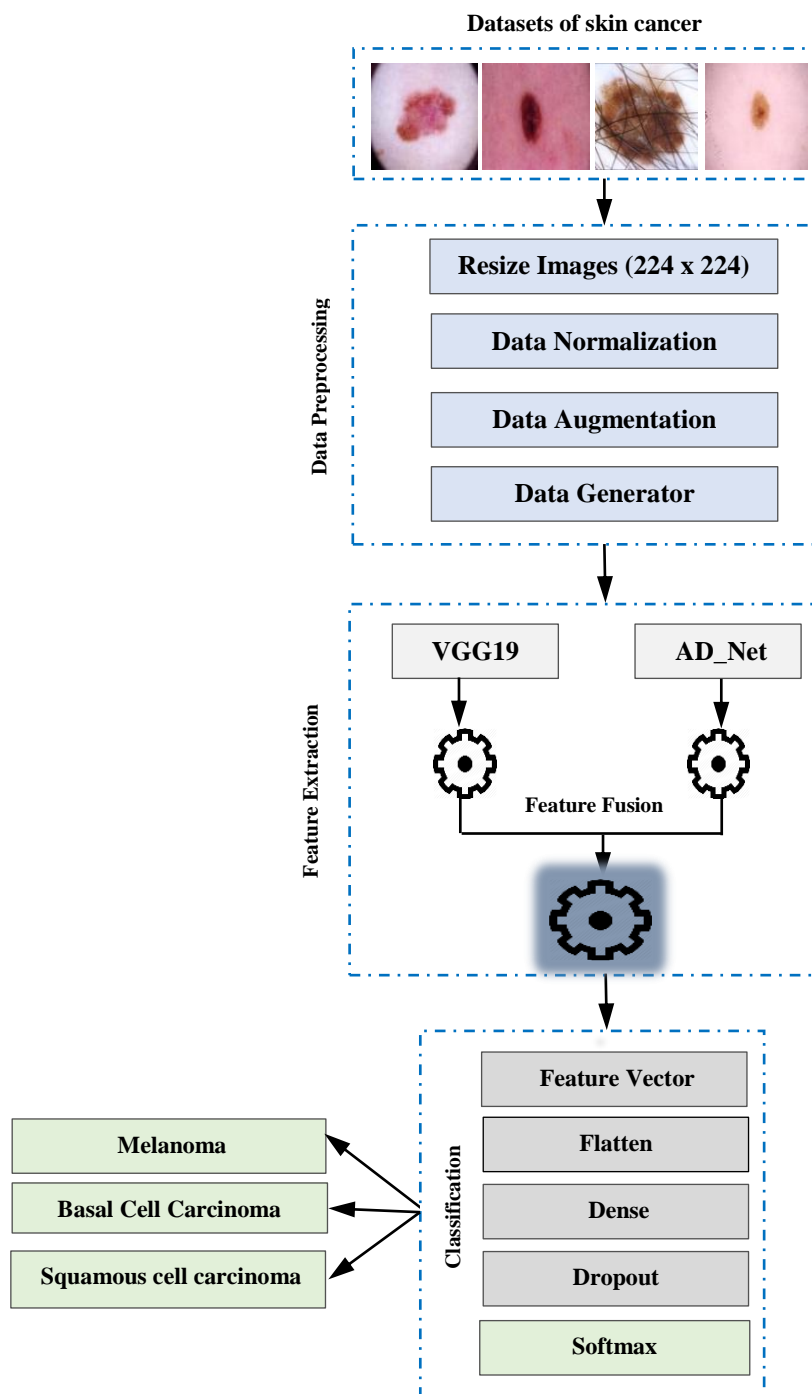


Figure 2. The architecture of Proposed ADNet.

4.2 Proposed approach ((Hybrid VGG19- ADNet Model for Skin Lesion Classification))

In this study, we present AD_Net, a hybrid model characterized by a lightweight architecture based on expanding the width of the network that contrasts with the depth-oriented hierarchical architecture of traditional networks. This allows it to process the image through multiple parallel internal paths to extract fine-grained features. It is specifically designed for analysing medical images. Its architecture consists of several layers. Starting with the input layer where the input image is cropped to 224 x 224 pixels. This helps preserve key information while minimizing the amount of computational resources required and ensuring compatibility with the model being

proposed at the same time. It makes it possible to analyse and process specific regions separately, which can be useful in a variety of computer vision tasks.

One of the most important parts of convolutional neural networks, also known as convolutional neural networks, is the convolutional layer. When this layer is applied to the output of its predecessor, an activation of the 2D maps of the filters it corresponds to is created. This is achieved by changing the height and width of the input volume. Each filter must have the same transparency level as the inputs. Furthermore, the dimensions of the outputs can be controlled by adjusting three sub-parameters: Zero Padding, Step, and Depth. These parameters are discussed in more detail below. These filters make it possible to capture a variety of features, such as lines, corners, edges, points, etc. This particular model uses ten convolutional layers, each based on three-by-three filters. Once each convolutional layer is complete, subsequent layers of batch normalization (BN) and corrected linear unit (ReLu) are combined. In addition, projection layers are included in order to minimize the amount of overfitting that occurs.

To achieve efficient functional integration, AD_Net and VGG19 are combined into a two-path hybrid model running on a single input, where the same image is sent to both models in parallel. The improved VGG19 network was introduced by removing the last three fully connected layers that were dedicated to classifying 1000 classes from ImageNet [18], and replacing these layers with a customized part of the base model architecture for proper adaptation to the current task. All remaining layers except the last six were frozen and made trainable to take advantage of the features learned from ImageNet and allow the upper layers to adapt to the characteristics of the melanoma images. VGG19 acted as a low-level feature extractor, being pre-trained, leveraging previous knowledge, and easily adaptable to new tasks while AD_Net skilfully learned specialized patterns. Figure 3 shows the layers for hybrid model.

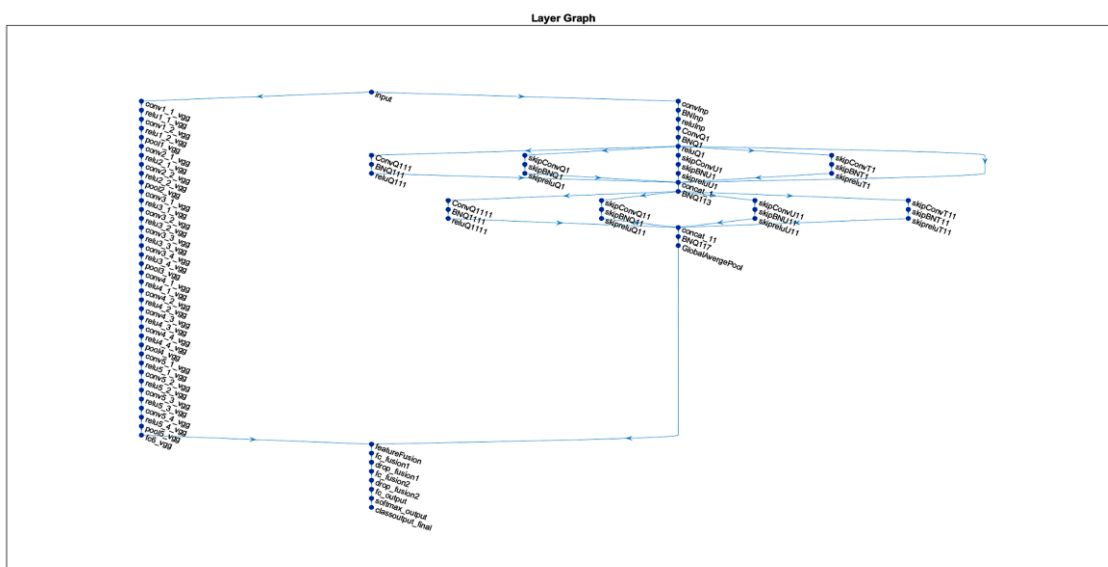


Figure 3. Layers of the AD_Net.

Where: Layers of the ADNet. Where: CONV=convolution layer, BN=batch normalize, Relu=rectified linear, Concat= concatenation layer, FC=fully connected layer, Drop=dropout layer.

This parallel training and fusion strategy enables better generalization across different skin tones, lesion shapes, and background textures, which may not be effectively captured by traditional CNNs alone. This improved the model's classification performance and reduced response time, without increasing the computational load. This parallelization was implemented through the multi-processing capabilities of GPUs such as) NVIDIA RTX 3070 using MATLAB.

4.3 Explainable Artificial Intelligence (XAI)

Since machine, learning systems are often considered closed boxes. Explainable Artificial Intelligence (XAI) is an important tool for understanding the decision-making process within these models. XAI enables designers, developers, and users to recognize the reasons behind a model's predictions. Both during and after training. This

enhances transparency and reliability, which is especially important in the environment of critical medical applications such as medical diagnostics.

In this experiment, XAI techniques were incorporated to interpret and analyze the functioning of the proposed model. Specifically, Grad Cam-type visual activation maps that visually highlight the most influential regions in the input image on which the model based its decision-making. These maps are displayed as a transparent thermal layer over the original image, allowing the identification of the regions that influenced the model's classification decisions. This method verifies that the model is focused on clinically relevant features. This reduces the likelihood of making wrong decisions based on irrelevant features. It also enhances users' confidence in AI-based diagnostic tools.

4.4 Experimental result and discussion

To evaluate the effectiveness of our proposal, we performed a number of experiments on the ISIC2019 dataset. Interpretable Artificial Intelligence (XAI) allowed us to identify the key elements that influence the model's predictions. Understanding their origins allowed us to identify potential areas for improvement. Using a number of common metrics to evaluate our experiment, such as F1 score, recall, and precision to evaluate our approach; the mathematical formulas for these metrics are given below.

- (1) Accuracy = $(TP+TN)/(TP+FN+FP+TP)$
- (2) Precision = $TP/(TP+FP)$
- (3) Recall = $TP/(TP+FN)$
- (4) F1_Score = $(Precision \times Recall)/(Precision + Recall)$

The system's performance was tested using true positive (TP), false positive (FP), true negative (TN), and false negative (FN) images. We tallied the number of photos that were correctly classified as pathological (TN) and the number of photos that were mistakenly classified as dangerous (FP) or pathological (FN). Next, we contrasted these figures with the quantity of typical and accurately recognized images (TP). The ratio of correctly identified cases to all labeled images was then determined using the accuracy metric derived from Equation 1. The test result displayed by the confusion matrix on the experiment's data is displayed in Figure 4.

	BCC_Images	MEL_Images	SCC_Images
BCC_Images	444	2	1
MEL_Images	2	446	
SCC_Images	6		442
True Class	BCC_Images	MEL_Images	SCC_Images
	Predicted Class		

Figure 4. Confusion matrix for testing our proposed model.

The model was trained using the Adam optimizer with a learning rate of 0,0003 and additional hyper parameters. Running 30 epochs produced the result, which had a measurement accuracy of 99.18%. Our deep learning approach's training process was shown in Figure 5.

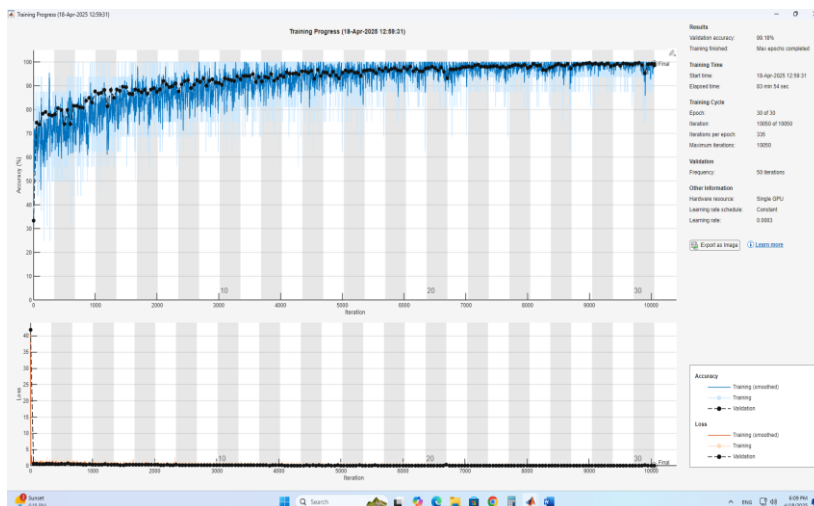


Figure 5. Final training our approach.

In Table 2, we can see how this study comparison to prior research. These findings conclude that our proposed approach surpasses existing models as an effective system for skin cancer detection, demonstrating its superior performance.

Table 2: Comparative Analysis of AD_Net with Related Studies.

Ref.	Year	Dataset	Precision	Recall	F1_Score	Accuracy
[7]	2022	ISIC_2019	92.19%	92.18%	92.18%	96.91%
[8]	2023	ISIC_2019	88.69%	88.90%	-	96.10%
[11]	2023	ISIC_2019	93.33%	100%	96.55%	97.56%
[12]	2024	ISIC_2019	98.31%	97.89%	98.10%	97.81%
Proposed ADNet	2025	ISIC_2019	98.0%	99.0%	99.0%	99.18%

Table 3 provides a thorough comparison between ADNet and modern networks for classification purposes, assessing their performance across several criteria and presenting an overview of each network’s classification capabilities of each network. The assessed networks were the suggested AD_Net, VGG16 (B4), Inception-v-3(B3), MobileNetV2(B2), and EfficientNetB0(B1).

Table 3: AD_Net’s classification performance is compared to that of contemporary networks.

Classifiers	Pre.	Rec.	F1-Score	Acc.
B1	91.05%	91.77%	88.39%	92.88%
B2	97.60%	97.25%	97.35%	97.23%
B3	96.0%	96.0%	96.0%	96.20%
B4	93.84	93.69%	93.72%	93.47%
Proposed ADNet	98.0%	99.0%	99.0%	99.18%

The five deep learning classifiers compared in Table 3 using four universal assessment criteria of precision, F1_score, recall and accuracy are EfficientNetB0, MobileNetV2, Inception-v-3, VGG16, and the suggested AD_NET. These criteria supply a thorough assessment of each system's classification effectiveness in medical imaging and other critical applications where sensitivity and specificity are important.

The AD_Net outperforms all assessment criteria, achieving the Precision (98.0%), recall (99.0%), F1 score (99.0%), and highest accuracy (99.18%). The results show great detection abilities, consistent performance, and good generalizability, highlighting their potential applications in major classification challenges. With 97.60% accuracy and 97.23% precision, MobileNetV2 performs exceptionally, exceeding 97% across all parameters. Its good balance of computational efficiency and classification accuracy indicates that MobileNetV2 is suitable for resource-constrained or real-time settings. Inception-v3 consistently scores 96.0% on the three main benchmarks due to its strong and well-designed architecture, with a slightly better accuracy of 96.20%. Though it runs a bit worse, VGG16 always produces decent results with 93.84% accuracy, 93.69% recall, 93.72% F1 score, and 93.47% precision.

Examining the specifics reveals that EfficientNetB0, although a lightweight and scalable choice, performs worse, especially in the F1 score of 88.39%. This implies a potential equilibrium between the complexity of the model and its classification effectiveness. The findings indicate that the suggested AD_NET beats earlier networks in consistently and accurately classifying. This underlines the capacity of specially designed models to produce outstanding outcomes on difficult classification problems. The hybrid approach lets the model acquire a more accurate and thorough knowledge of skin disorders by combining several, occasionally unique traits from different methods. This enhanced its capacity to tell between several skin disorders. This strengthened its capacity to tell one skin condition from another. Grad-CAM visualizations were used to identify the region's most influential to the model's predictions. These heat maps provided intuitive visual interpretations that support the reliability of the model's decisions.

Figure 6 shows the model's focus on the most affected regions. This supports the model's ability to address biases associated with demographic factors and environmental conditions. The model accomplishes this by adjusting for diverse individual characteristics and improving understanding through a comprehensive set of relevant features.

However, we did not include quantitative interpretations, such as overlap with expert comments or statistical metrics, due to the lack of accurate, dermatologist-annotated salience maps that can be relied upon for this type of testing. We acknowledge the importance of including quantitative interpretations in future studies to enhance the transparency and clinical applicability of the suggested framework. This proposed evaluated the hybrid AI model's real-time capabilities using various performance metrics. With an NVIDIA RTX 3070, inference time that is the duration between image input and prediction was measured at 20ms, indicating that it is appropriate for use in medical settings.

The model cuts processing time by utilizing parallel dual-path hybrid architecture (VGG19 and ADNet). System efficiency was shown by recognition performance of approximately 50 frames per second (FPS). Although edge devices have not yet been tested, future deployment is planned. Parallel structures enhance reactivity by extracting features simultaneously. Multiprocessing was implemented in MATLAB R2023a. Additionally, the design promotes scalability by distributing processor paths, enhancing speed and preventing bottlenecks.

Figure 7 shows the model's predictions. The first column shows the original images of the data. The second column shows the disease type and the prediction accuracy of the model based on the test images. The third column uses a heat map overlay on the original image to illustrate the affected and critical locations.

Although current evaluations were conducted on the ISIC2019 dataset, the proposed model's flexible architecture and efficient learning capabilities enable it to integrate more diverse and comprehensive datasets, including ISIC2020, with exceptional scalability. It is well suited for integration into clinical IoT systems thanks to its rapid response and stealth architecture, facilitating remote diagnosis and immediate analysis of skin lesions.

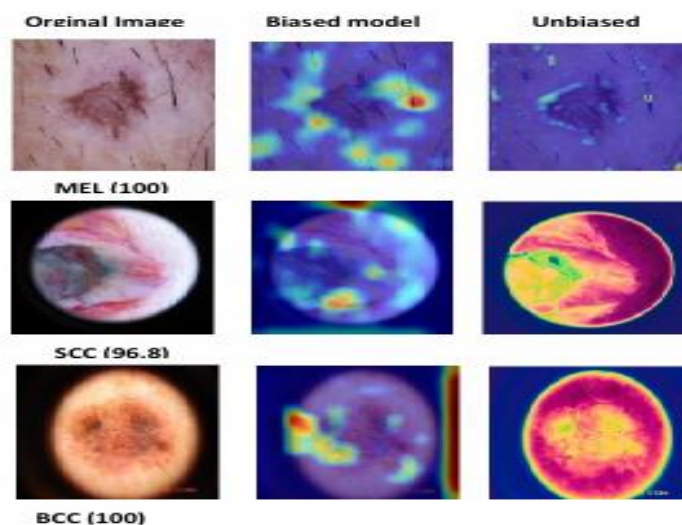


Figure 6. Heat map highlights risky areas.

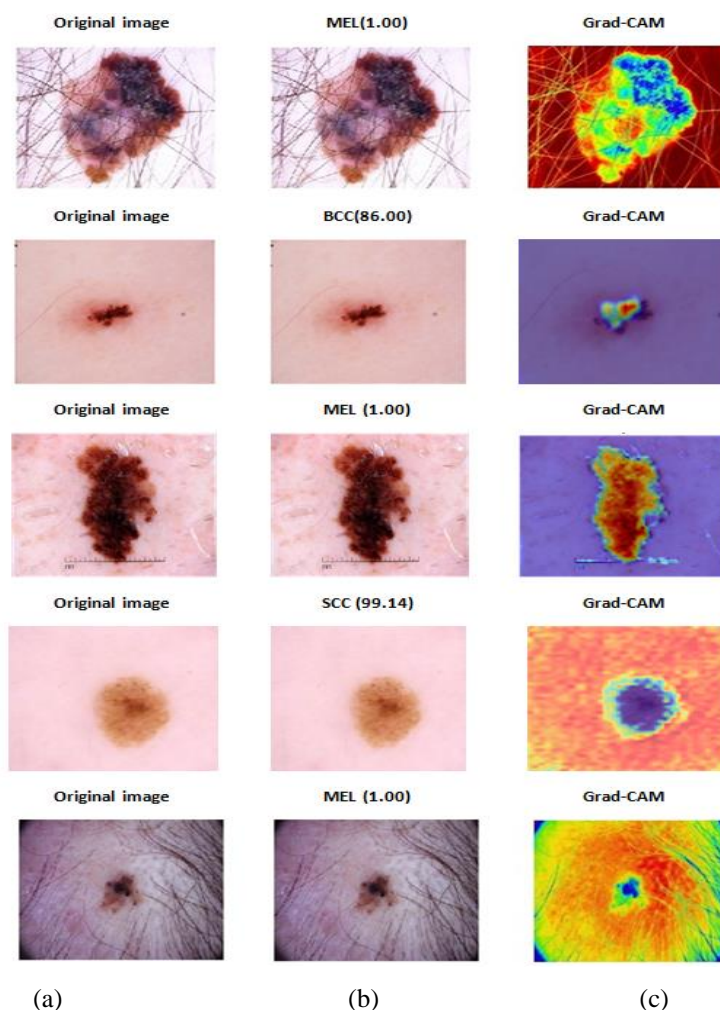


Figure 7. Genuine images from the ISIC2019 dataset, (a) original images, (b) prediction accuracy, (c) Heat map highlights risky areas.

5. Conclusions and future directions

Our study presents an innovative hybrid deep learning architecture that integrates VGG19 and AD_Net at the feature level to improve early skin cancer detection.

This parallel training and integration strategy enables better generalization across different skin tones, lesion shapes, and background textures, which may not be effectively captured by traditional CNNs alone. Biases related to environmental factors and demographic characteristics are lessened by this approach.

The proposed approach facilitates enhanced classification of three of most deadly forms of skin cancer in humans: Melanoma (MEL), squamous cell carcinoma (SCC), and basal cell carcinoma (BCC).

We compared our model (AD_Net) with four benchmark to evaluate its effectiveness. It achieved an accuracy rate of 99.18%. The finding of this study demonstrates that new model is an effective tool for skin cancer classification, were based on dermoscope images. Experts' ability to rapidly identify, differentiate, and diagnose various types of malignant skin cancer improves, significantly facilitating early treatment. VGG19 helps accurately extract low-level features. While AD_Net learns specialized patterns specific to skin lesion classification,

Incorporating features at the feature level significantly reduces inference, enabling rapid predictions suitable for real-time clinical settings. Furthermore, the model is expected to benefit further from the availability of realistic datasets that include a wider range of diagnosed skin cancer cases. The addition of images from a wider range of skin types and imaging tools could also improve the model's generalizability and reliability across many different clinical settings and populations around the world.

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