https://doi.org/10.65542/djei.v2i1.26
Dasinya Journal for Engineering and Informatics. **2026**, *1*, 3.

Review

An In-Depth Review of Leveraging Deep Learning Advancements for Enhanced Skin Cancer Detection and Classification

Ahwaz D. Hayder [1,*], Jwan Najeeb Saeed [2]

[1] Information Technology Management Department, Technical College of Administration, Duhok Polytechnic University, Duhok, Kurdistan Region, Iraq.
[2] Artificial Intelligence Department, Technical College of Duhok, Duhok Polytechnic University, Duhok, Kurdistan Region, Iraq.
* Correspondence: ahwaz.hayder@dpu.edu.krd

Abstract

Skin cancer is a prevalent form of cancer caused by the abnormal growth of skin cells, most commonly resulting from exposure to ultraviolet radiation. Early detection is essential for improving clinical outcomes, highlighting the need for advanced and reliable diagnostic approaches. Traditional diagnostic methods often face significant challenges due to high variability arising from the subjective nature of assessments and their reliance on specialists, whose performance is constrained by conventional techniques such as dermoscopy and histopathology. Recent advancements in deep learning have significantly transformed the field of dermatology by enabling automated and reliable skin lesion classification. This study presents an in-depth review of state-of-the-art deep learning techniques, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), transfer learning, and generative adversarial networks (GANs). In addition, the study examines the application of vision transformers (ViTs), which have demonstrated strong capabilities in capturing comprehensive contextual information in skin lesion analysis. Furthermore, this review explores the integration of explainable artificial intelligence (XAI) as well as hybrid and collaborative strategies to enhance model interpretability and reliability. Therefore, this review aims to establish a solid foundation for future research in the automated classification of skin cancer.

Keywords: Deep learning; skin lesions classification; convolutional neural networks; transfer learning; explainable AI.

1. Introduction

The skin, the largest organ of the human body, serves as a crucial barrier against infections, thermal damage, and ultraviolet radiation. Despite these protective functions, cancer remains a profound threat to human health. Among the diverse forms of cancer that can develop, skin cancer stands out as one of the most aggressive and rapidly proliferating malignancies[1]. A significant number of skin cancers originate in the outer layer of the skin. Skin cancer arises when skin cells multiply and spread without regulation. Typically, new skin cells are produced to replace old or damaged ones [2]. However, when this process malfunctions, cells can proliferate rapidly and chaotically. These cells are referred to as a tumor because they form a cluster of tissue. Various factors can contribute to this condition, including alcohol consumption, tobacco use, allergic reactions, viral infections, environmental changes, and exposure to ultraviolet (UV) radiation. Millions of new cases of skin cancer are discovered worldwide each year, with melanoma being the most common type. Improving patient survival rates requires early diagnosis of malignant skin lesions. However, traditional

Received: October 31, 2025; Revised: December 28, 2025; Accepted: December 31, 2025; Published: January 16, 2026; Available online: January 16, 2026.

techniques such as tissue examination and skin examination which are often used in clinical practice have been relied upon for diagnosis. Although these techniques are useful, they require highly skilled professionals and are often interpreted subjectively, which may vary diagnostic accuracy [3]. Especially in the detection of malignant melanomas, where timely treatment is crucial to a patient's prognosis, this intrinsic subjectivity can contribute to diagnostic variability and, in some cases, delayed diagnosis or misdiagnosis [4], [5]. Therefore, there are inherent drawbacks to traditional skin cancer diagnostic techniques as they are based on specialized knowledge and are subject to change due to different interpretations. Furthermore, scaling up diagnostic services to meet the growing demand for skin cancer screening globally may be challenging due to the resource-intensive nature of these technologies [6]. The A, B, C, D, E rules are guidelines for assessing moles for potential skin cancer, especially melanoma. A (Asymmetry) indicates that if you draw a line through the mole and the halves don't match, it could be concerning. B (Border) refers to irregular, jagged, or blurred edges, unlike the smooth borders of normal moles. C (Color) highlights moles with multiple colors or shades as potentially problematic. D (Diameter) notes that moles larger than 6 millimeters should be evaluated, though smaller ones can also be concerning. E (Evolving) emphasizes monitoring any changes in size, shape, color, or symptoms like bleeding or itching [4]. Significant advances in DL and artificial intelligence (AI) have dramatically transformed dermatology in recent years. The most advanced technology for identifying skin lesions is CNNs, which allow models to automatically learn complex patterns from large image datasets. Khan et al., [7] and Alipour et al. [8] have demonstrated remarkable performance in lesion classification, reaching high accuracy rates and significantly reducing the subjectivity associated with traditional diagnostic methods. CNNs have been frequently used to deal with problems of constrained or imbalanced medical datasets, especially when combined with sophisticated preprocessing methods such as data augmentation and transfer. However, the availability of large, well-labeled data sets, which are essential for training AI models, is another major hurdle. Often, medical imaging datasets are imbalanced and insufficient for robust model training, which limits the effectiveness of automated diagnostic systems learning [9], Hasan et al. [10] investigated how deep learning can be used alongside cutting-edge imaging modalities to overcome the drawbacks of traditional diagnostic procedures and open the door to more effective and accessible skin cancer screening. It also describes new research approaches and the latest developments in automated and interpretable diagnostic systems by addressing special difficulties related to data quality, model interpretability, and clinical integration. This distinct viewpoint provides insightful information that advances the topic by adding to the existing body of knowledge. Consequently, this work aims to:

- Synthesize the most recent advancements in computer vision techniques applied to skin cancer diagnosis,
- Focusing on key methodologies, datasets, and challenges.
- Analyzing recent developments and recommending strategies to boost the effectiveness, transparency, and integration of AI tools in skin cancer detection.

This review is structured to provide a comprehensive analysis: Section 2 delves into the theoretical foundations, covering various skin cancer types and prominent datasets. Section 3 explores state-of-the-art deep learning techniques for classification and detection, alongside critical performance metrics. Section 4 addresses the key challenges and limitations of applying deep learning to skin infection analysis. Finally, Section 5 concludes with impactful insights and forward-looking recommendations to guide future advancements in the field.

2. Theoretical Background

2.1 Skin Cancer Types

Skin cancer types vary based on the initial cell affected and the level of malignancy, with each type displaying unique characteristics. It primarily consists of two types: Melanoma and Non-Melanoma. Non-melanoma skin cancers are classified into two main types: basal cell carcinoma and squamous cell carcinoma. Both types begin in the epidermis, which is the outermost layer of the skin. It's also important to have a clear understanding of the various types of skin cancer and work with the right datasets for classification to build accurate and dependable diagnostic models. This section discusses the main types of skin [11].

- Basal Cell Carcinoma (BCC): The most common type of skin cancer develops from the basal cells of the epidermis. On sun-exposed skin, it usually appears as flat, scaly patches or pearly nodules. While it rarely spreads, leaving it untreated can lead to significant damage in the affected area [11] , [12].
- Squamous Cell Carcinoma (SCC): It's the second most common skin cancer, forming in the squamous cells of the epidermis. It often appears as a scaly patch, a hard red lump, or a poorly healing ulcer. Early recognition is crucial because squamous cell carcinoma can spread if left untreated [13].
- Melanoma: Although less common than BCC and SCC, melanoma is the most serious type of skin cancer that begins in melanocytes. It often appears as a new or growing mole more than 6 mm in diameter, with uneven borders, asymmetry, and a range of colors. Melanoma requires rapid identification and treatment because it can spread quickly to other areas of the body [14].

2.2 Skin Cancer Datasets

Skin cancer datasets are vital for advancing research in dermatological diagnostics. These datasets typicallycontain annotated medical images of various skin cancer types. These datasets became pivotal in training and testing deep learning models for detecting skin diseases. To this end, the ISIC datasets from 2016 up to 2020 contributed towards improving the research pertaining to classification and detection of skin lesions. The ISIC 2016 dataset started with 2000 images from 7 classes focusing primarily on melanoma and other benign skin tumors. With every release, not only has the dataset increased the number of images, but also the variety of skin conditions [15] ,[16]. The HAM10000 dataset includes 10,000 dermatoscopic samples of pigmented skin lesions from people from different racial backgrounds. The PH2 dataset includes 200 dermoscopic images of melanocytic lesions comprising 80 common nevi, 80 atypical nevi, and 40 melanomas. This collection is of interest for researchers who intend to analyze different strategies of segmentation and classification [11]. The DermIS dataset with its 96 samples is applied for teaching AI models for analysis of lesions. This dataset serves as a significant compilation of data toward the development and refinement of algorithms with complex outlines that require precise detailing for accurate diagnosis [17], [18]. DermQuest is an enlarged dataset of 1,653 dermatoscopic images tailored to improve machine learning training. Increasing both the quantity and variety of images aids in the creation of more dependable diagnostic instruments, especially concerning nevi. [19] The Mpox Skin Lesion dataset has 1,428 images which are labeled and important for developing diagnostic models [20] as shown in table 1.

Table 1. The summary of the popular skin lesions datasets.

Dataset Name	#Images	# Classes
ISIC2016	**900**	**7**
ISIC2017	**2000**	**3**
ISIC2018	**10,015**	**7**
ISIC2019	**25,331**	**8**
ISIC2020	**33,126**	**9**
HAM10000	**10,015**	**7**
DermIS	**96**	**2**
DermQuest	**1,653**	**2**
Mpox Skin Lesion	**1,428**	**2**
PH2	**200**	**3**

3. Deep learning in skin cancer detection and classification

Change in the identification and classification of medical problems with the use of imaging technologies such as dermascopy has proven to be very helpful. DL, for example, has developed an automated procedure for feature extraction which enhances precision and constancy in the diagnosis of skin cancer [21] ,[22].

3.1 Convolutional Neural Networks and Transfer learning

The CNNs can scan large amounts of visual data and gradually extract features such as edges, textures, and colors from dermatoscope images makes them popular in skin lesion classification. It helps medical imaging in dermatology by automatically recognizing and analyzing hierarchical features in images with an accuracy like that of dermatologists. The convolutional and pooling layers required to evaluate dermoscopic images and extract important features such as edges and textures in the condensed CNN design are illustrated in Fig.1. The fully connected layers then use these features to determine whether a lesion is benign or cancerous [9], [23] demonstrated how CNNs can be used to improve diagnostic accuracy by classifying and segmenting skin lesions from a variety of imaging modalities, such as medical ultrasound. significantly enhanced classification performance and showed notable gains in accuracy. The utility of CNN frameworks for lesion segmentation and classification was highlighted by [2], especially when using well-known datasets such as ISIC and HAM10000. The combination of deep metric learning and attention techniques which focus on distinguishing between similar classes and identifying differences within classes is a new development in CNN applications.

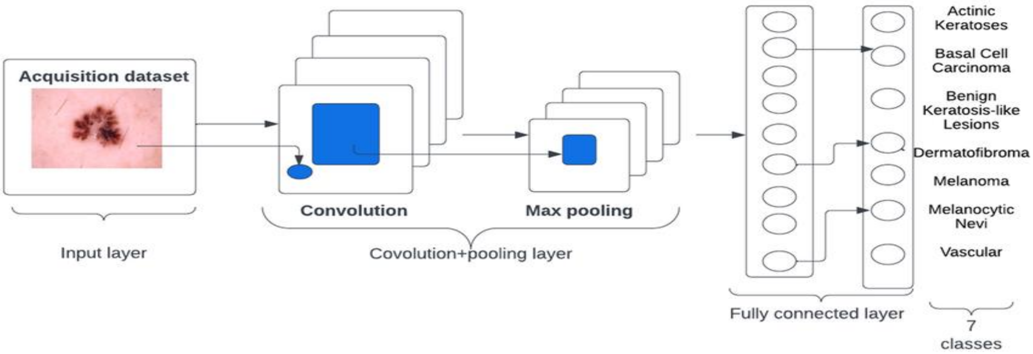

Figure 1. A Sample of CNN architecture for skin classification.

Mobile phone-based AI technologies play a crucial role in skin cancer classification by leveraging the accessibility and portability of smartphones combined with AI-driven image analysis. These technologies enable early detection by capturing high-quality skin images through phone cameras, which are then processed using machine learning models to identify cancerous lesions. [24] introduced SkinLesNet, a multi-layer deep CNN to classify three different types of skin lesions using smartphone apps. The PAD-UFES-20-Modified, HAM10000 and ISIC2017 datasets were used to train the model. However, although the study emphasizes cutting-edge methods, the complexity of the model may make it difficult to apply in real-time clinical settings where interpretability and speed are essential. In the same context, [25] built a mobile application for self-examination of monkeypox lesions and rash stages. For the classification task, the EfficientNet model was used, and produced accuracy rates of 97% for classifying the stage of the rash and 95% for identifying the lesion. However, demographic changes may not have considered, including skin color and type, this could affect how well the model performed. Similarly, a unique lightweight deep learning architecture suitable for real-time applications on mobile healthcare systems was presented [26] with a large scale ShuffleNet architecture for classification after applying a novel hashing algorithm based on cumulative moments and entropy-based weighting. It performed exceptionally well on the HAM10000 and ISIC2019 datasets. Several machine learning methods were investigated [27] and [28] , iincluding supportvector machines (SVM), logistic model and tree approach to depict how machine learning can help in early detection and diagnosis of skin cancer by evaluating different models on a custom dataset. However, differences in image quality resulting from different imaging devices used in dermatoscopy may affect model performance and lead to inconsistent results in different clinical settings.[29] proposed a unique method for skin cancer classification, using the Segmentation Anything Model (SAM) for semantic segmentation of skin lesions on ISIC2018 and HAM10000 datasets for validation and training after sophisticated preprocessing techniques including boosting and normalization. However, class imbalance in the data set can affect study results and lead to models that perform poorly on underrepresented groups. Thus, utilizing unbalanced dataset may lead to biased results that favor identification of the most prevalent types of lesions. Therefore, researchers in [12], [30], [31],[32], [33] implemented data augmentation strategies to solve this issue and enhanced the classification performance. Priyanka et al. [34] investigated the use of multispectral autofluorescence lifetime imaging to classify pigmented skin lesions at the pixel level. The maFLIM approach enables imaging of skin lesions without labels, helping to distinguish between benign and malignant cases. Researchers found that a deep neural network model achieved the highest accuracy, with 76.84% sensitivity and 78.29% specificity. In determining losses, the function is instrumental for the model towards distinction accuracy for benign and malignant lesions. In the detection accuracy improves and reduces false positives and false negatives, more reliable skin cancer classification is achieved. Thus, a loss function was built in [35] to boost skin lesion recognition in deep learning models using domain knowledge. By improving distinguishing skills of varying lesions, MDKLoss is further enhancing models' performance. This was implemented in ISIC 2018 and ISIC 2019 datasets, with best accuracy of 91.6% and 87.6%, in that order.

Transfer Learning (TL) enhances model performance with limited data by leveraging other models' pre-trained knowledge from vast datasets. The model uses the features it has learned with little data on the new but closely related tasks, resulting in requiring less data, while increasing the training, generalization, and speed of the model. Transfer learning allows for highly accurate models even in limited-resource settings, making skin lesion classification more efficient and scalable [36], [37]. For instance, the pre-trained CNNs have been developed on large datasets such as ImageNet and optimized on smaller medical datasets such as HAM10000 and ISIC. The model gets better at a new task by using what it learned from a previous one. It fine-tunes itself by adjusting its internal settings (weights), which helps it perform the new task more accurately [38]. This method, even with minimal clinical data, accelerates model training and enhances performance on skin lesion classification tasks [39]. Profile et al. [40] explored are conducting a comparative analysis to evaluate different deep learning models for skin disease classification. The study uses a custom dataset to evaluate the performance of models such as CNN and DenseNet. The results show that when it comes to identifying different skin disorders, CNN had the best classification accuracy as 91% of the methods tested.

A combination of the Xception and InceptionV3 architectures was proposed in by [41] for early diagnosis of skin lesions. Using data augmentation techniques on the HAM10000 dataset, the study addresses class imbalance and achieves high accuracy (98%) on balanced data. When it comes to classifying complex skin lesions, a collective approach is superior to individual models. The study helps increase the accuracy of early diagnosis in classifying skin lesions, especially for difficult multi-category functions. However, the limited focus of the study on specific types of lesions may limit the applicability of the findings to other skin problems. Similarly, [10] utilized DenseNet201 and ResNet52V2 with training images achieving 95% accuracy and test images achieving 91% accuracy. ResNet152 was implemented by [42] that incorporating data augmentation for lesion diversity. Trained on the ISIC 2018 dataset, the model achieved 87.42% specificity. [43] proposed a dual stream deep learning model that integrates local, contextual, and hierarchical information to classify skin lesions. The architecture extracts multi-scale features from endoscopic images by integrating a custom CNN with modified DenseNet-169. The model outperformed traditional techniques with an accuracy of 93.2% after training on the HAM10000 dataset. [7] presented a model combined the features of MobileNet-V2 and DarkNet-19 with a hybrid firefly optimization method using ISIC2018 dataset, the study's accuracy rate of 89% demonstrated the effectiveness of fusion-based DL models for medical image classification. [44] reported the melanoma, SCC, and BCC are the three predominant forms of skin cancer based on EfficientNet architecture. The study examines different iterations of the EfficientNet model (from B0 to B7) using a custom dataset. With an accuracy rate of 79.69%, the EfficientNet-B4 model showed the best performance. Meanwhile, [45] developed a multi-stage, multi-layer CNN-based system for identifying and classifying skin lesions, this technique first classifies lesions as benign or malignant and then uses transfer learning to classify subcategories more accurately. Using the ISIC2018 dataset for training, the model achieved a high classification accuracy of 93.4% for primary classification and 96.2% for subclassification. Comparing this multi-stage method with previous CNN-based techniques, the accuracy is significantly improved, and the training time is reduced. Metaheuristic techniques can contribute to obtain high performance via its efficiency in selecting appropriate features. Therefore, some studies explored the optimization-driven approaches for skin cancer diagnosis, highlighting the synergy of deep learning and metaheuristic techniques. For instance, [4] used MobileNet for feature extraction, U-Net for segmentation, and Cat Swarm Optimization (CSO) for hyperparameter tuning, improving classification accuracy and demonstrating the potential of optimization strategies for enhancing diagnostic precision. Similarly, [16] incorporate a ResUNet in its hybrid form model with Ant Colony Optimization (ACO) for skin lesion segmentation, achieving 95.8% accuracy as shown in table 2.

Table 2. The summary of state of the art based on CNN and transfer learning techniques.

Ref.	Model	Datasets	#Classes	Accuracy%
[4]	**ASCDC-CSODL**	**ISIC2017** **HAM10000**	**3**	**92.22** **98.48**

[10]	**ResNet52V2, DenseNet201**	**HAM10000**	**7**	**91**
[12]	**Customized CNN**	**HAM10000**	**7**	**97.78**
[16]	**Hybrid ResUNet**	**ISIC 2018**	**3**	**95.8**
[24]	**SkinLesNet (ResNet50 and VGG16)**	**ISIC201, HAM10000, PAD-UFES-20**	**7,3,2**	**92 ,90 ,96**
[25]	**EfficientNet**	**MSLD**	**4**	**0.97**
[27]	**GAN and U-Net**	**ISIC 2020**	**3**	**84.5**
[29]	**InceptionV3,DenseNet, Xception,VGG16, EfficientNetV2**	**HAM10000, ISIC 2018**	**7**	**85.33%**
[30]	**Federated learning**	**ISIC 2018, PH2**	**7, 3**	**98**
[31]	**DenseNet**	**ISIC**	**7**	**88.6**
[32]	**LesNet(DenseNet,VGG-16,and Inception)**	**HAM10000, ISIC-2019**	**7**	**98 94**
[33]	**SqueezeNet,**	**ISIC-2019**	**8**	**71.80 98**
[34]	**SVM, RF and NN**	**maFLIM**	**2**	**78.29**
[35]	**CNN and MDKLoss**	**ISIC 2018 -2019**	**7,8**	**91.6 87.6**
[40]	**ResNet18**	**ISIC**		
[41]	**Oriented IncepX squad**	**HAM10000**	**7**	**98**
[42]	**ResNet152**	**HAM10000**	**7**	**87.42**
[43]	**Dual-Track based DenseNet**	**HAM10000**	**7**	**93.2**
[44]	**EfficientNet**	**ISIC 2019**	**3**	**79.69**
[45]	**MMCNN**	**ISIC2018**	**5**	**96.2**

3.2 Recurrent Neural Networks and Long Short-Term Memory

Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are great for working with data where the order really matters. This is different from CNNs, which are good at dealing with images. In dermatology, this ability is especially helpful since diagnosing skin issues relies on keeping an eye on how lesions change over time. By combining CNNs and LSTMs, these hybrid models take advantage of both spatial and temporal data, allowing for a more thorough and accurate analysis. [42] and [46] explained how these hybrid models dramatically increase diagnostic accuracy by tracking changes over time as well as capturing static image features. By combining clinical and imaging data, these models provide individualized diagnostic insights and are essential for long-term monitoring. The utility of RNNs and LSTMs in addressing specific problems such as class imbalance and within-class variation has been comprehensively studied in [46],[3],[4], and [47]. These models enhance reliability and minimize errors by effectively recognizing intricate lesion patterns and understanding how they evolve over time. In addition, [5] showed that a hybrid CNN-RNN model based on ResNet-50 can identify complex skin lesions from large datasets with remarkable accuracy. Researchers in [9], [46], [26], and [22], showed that despite the progress, there are still a lot of challenges to tackle before RNNs and LSTMs can be really used in the real world. Without proper hardware support, getting these models to work in real-time can be tough because they take a lot of computing power for training and need large, well-labelled datasets. Furthermore, dispersed diagnosis may be possible using lightweight, mobile-friendly models, but a balance must be struck between diagnostic accuracy and computing efficiency as shown in table 3.

Table 3. The summary of models based on RNNs and LSTM.

Ref.	Model	Datasets	#Classes	Accuracy%
[3]	RNN	Custom Dataset	5	84.7
[5]	(CNN-RNN) based ResNet-50	ISIC	9	94.48
[9]	CNN + LSTM	ISIC 2016-2017, PH2	3	89.7
[26]	RNN + lightweightCNN	HAM10000,ISIC 2019	2	90.2
[39]	LSTM and TL	DermIS, DermQuest	2	97.9 97.4
[46]	LSTM and Ensemble CNNs	ISIC 2018	7	88.5
[47]	Ensemble Model Based on LSTM	Custom Dataset	7	90.5
[48]	Hierarchical LSTM	Custom Dataset	3	86.3
[49]	Ensemble RNN	ISIC 2020	7	88.9
[50]	RNN and LSTM	ISIC 2019	8	84.5

3.3 Generative Adversarial Networks (GAN)

Generative Adversarial Networks (GANs) it is a modern class of deep learning models that primarily aims to produce synthetic data that closely mimics real data as shown in Fig. 2. And has two main parts as follows:

- Generator (G): Using random noise inputs, the generator creates synthetic samples. Its goal is to generate data identical to real-world data. This suggests the production of realistic dermatoscope images that can be used to supplement scarce data sets in the context of skin cancer detection. As the generator gains knowledge from the discriminator's feedback, it continually improves its output and delivers better performance in [51], [52], [53].
- Discriminator (D): The task of the Discriminator is to evaluate synthetic samples (generated by the generator) and real data samples (from the training data set). It produces a probability score that indicates whether the sample is authentic or not. In order to help the generator learn how to present more convincing data, the discriminator is taught to maximize its accuracy in distinguishing between the two [54], [55]. Two neural networks that make up the architecture, are trained simultaneously and competitively to produce a reliable data clustering system [22].

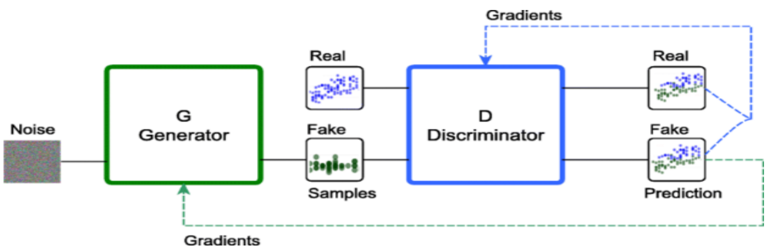

Figure 2. General GAN architecture [51].

In dermatology, GANs have been widely used, especially to improve skin cancer detection methods. Among the notable applications are firstly data augmentation since GANs may produce synthetic dermatoscopy images, helping to alleviate the problem of data scarcity, which is often a major bottleneck in medical imaging. GANs allow deep learning models to learn more general features by producing more training samples [53]. Secondly, image enhancement because GANs can enhance the quality of existing images and produce new data to increase the accuracy of diagnosis. The authors conducted in [17] showed that GANs can successfully improve the accuracy and clarity of a dermoscopy image, which will allow CNNs to be trained to classify skin cancer. [52] used a unique GAN design to reduce artifacts and improve the clarity of dermoscopy images. Although they were able to extract features more effectively, the effectiveness of their method was mostly dependent on the quality and diversity of the training images. In addition, [53] showed that using GAN to produce high-resolution synthetic images significantly improved classification accuracy, although there was still a risk of overfitting due to insufficient representation of real-world data. The applications of

GANs extend to improving image quality as well. [12] and [55] investigated hybrid models that combine GANs with other deep learning methods. GAN-generated data enhanced the training results and complement real-world datasets in [18]. However, a critical drawback is that for the images generated to be useful, they must faithfully depict the actual data, which can be difficult to do on a regular basis. When taken as a whole, these results demonstrate the revolutionary potential of GANs in medical imaging while simultaneously drawing attention to the problems that need to be solved to maximize their effectiveness in clinical settings. [56] presented SCDC-Net, a DL network for TL-based skin cancer classification. For better lesion segmentation, the model combines GAN and hybrid U-Net, to address issues such as hair artifacts that often affect classification accuracy. The model was able to capture color, texture and statistical information using techniques such as discrete wavelet transform (DWT) and gray level co-occurrence matrix (GLCM) to extract features on the ISIC-2019 dataset and reached an accuracy of 96% as shown in table 4.

Table 4. A summary of skin cancer classification models using GANs.

Ref.	Model	Dataset	#Classes	Accuracy %
[12]	Optimized CNN	HAM10000	7	97.78
[17]	Unrolled GAN	Dermoscopic images	3	96.60
[18]	CGAN	Real-world medical datasets	2	95.30
[51]	Vanilla GAN	Various medical datasets	3	95.93
[52]	WGAN	Dermoscopic images	3	96.03
[53]	DCGAN	Customized dataset	2	93.5
[55]	T-ResNet50 + STGAN	HAM10000	2	98.34
[56]	SCDC-Net	ISIC-2019	8	96

3.4 Vision Transformers (ViTs)

Vision Transformers (ViTs) leverage attention mechanisms to analyze images differently from CNNs, allowing them to capture long-range relationships between pixels. This ability makes them particularly effective in detecting and segmenting complex lesions like melanomas, which often have irregular shapes and indistinct boundaries [57]. Researchers have also explored hybrid models that integrate CNNs with other architectures, such as RNNs or ViTs, leading to even more promising outcomes in medical image analysis. [58] presented a hybrid DL model that outperforms traditional CNNs by achieving better segmentation and classification accuracy for skin cancer detection to classify skin lesions. An efficient pseudo-learning-based structural hierarchical representation was presented in [48], improving classification accuracy while reducing computational complexity. An overview of the hybrid GAN-CNN model workflow is shown in Figure. 3, [39].

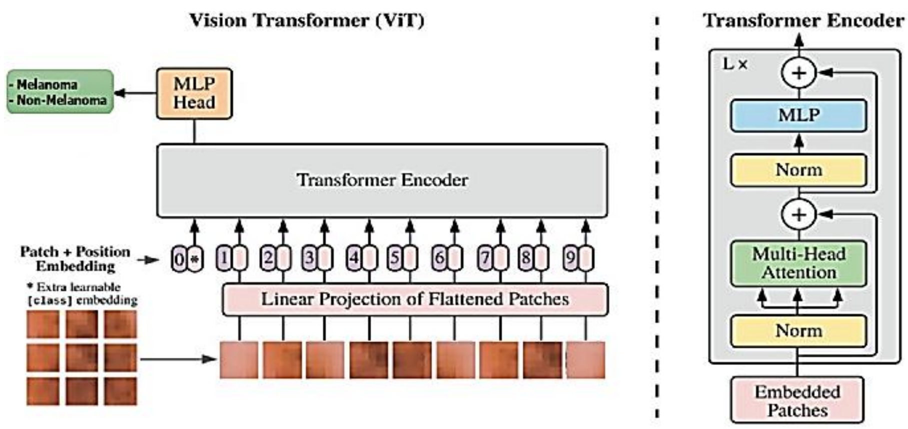

Figure 3. The general ViT structure.

A method that combining the Segment Anything Model (SAM) and the ViT models for skin cancer segmentation and classification was proposed in [59] . It utilized Google's ViT patch-32 model, the model obtained an accuracy of 96.15% and is highlighted the effectiveness of transformer models. [60] used ViT and presented a DL_based architecture on HAM10000 dataset reaching a classification accuracy of 94.7%, the ViT model was better than traditional CNN-based methods. [61] developed ViT-Grad-CAM model for prediction and classification of skin lesions. It provides enhanced multi-class classification capabilities. With an accuracy of 97.28%, ViT-Grad-CAM improved detection of malignant lesions after training on the HAM10000 dataset.[62] proposed the use of transformer-based DL to capture spatial dependencies in image data, the study applies the self-attention mechanism of transformers on a large, combined dataset from ISIC 2020 and custom sources. With a test accuracy rate of 86.37%, the model demonstrates that transformer networks can handle complex, multi-class skin lesion datasets. [63] created a multimedia educational framework that combines patient metadata with dermoscopy image analysis to analyze skin lesions. With up to 99% accuracy, the ViT-based method leverages data from multiple imaging modalities as shown in table 5.

Table 5. The ViT-based models.

Ref.	Model	Datasets	# Class	Accuracy%
[59]	**ViT & SAM**	**HAM10000**	**2**	**96.15**
[60]	**ViT**	**HAM10000**	**7**	**94.7**
[62]	**DNN and ViT Basis**	**ISIC 2020,2018**	**7**	**86.37**
[63]	**ViT**	**HAM10000**	**7**	**99**

3.5 Attention Mechanisms and Explainable AI (XAI)

Traditional machine learning models often lack transparency, making it hard to understand their predictions. This opacity reduces trust and hinders their adoption and use. Recently, machine-learning systems can explain their reasoning, highlight strengths and weaknesses, and predict future behavior. This is achieved by developing explainable models and using advanced human-computer interfaces to present clear, useful explanations to users. Explainable artificial intelligence (XAI) methods, including gradient-weighted category activation mapping (Grad-CAM), highlight the most important image regions to visually explain model predictions [48]. In medical settings, transparency is crucial because practitioners must trust and understand how a model makes decisions. XAI helps solve this challenge by making DL models less of a "black box" in healthcare [47]. It enhances physician confidence in AI-based diagnoses by increasing the transparency of model predictions [39].

Attention mechanisms boost DL accuracy and interpretability by helping models focus on key image areas, improving lesion classification by identifying important regions in the image [9]. The researcher in [64] investigated how Grad-CAM can improve the interpretability of CNNs for skin cancer classification. It proves that providing visual explanations for decision making using AI enhances the reliability and confidence of automated systems. This helps dermatologists understand why specific diagnostic findings occur. Author was An experiment in [65] has emphasized how Grad-CAM can be combined with CNN architectures aiming to address class imbalance, a common problem in medical image analysis. It shows how model performance is improved when Grad-CAM is combined with optimization algorithms such as Adam and RMSprop which reduces loss while improving classification accuracy. Additionally, it has been revealed in [66] that Grad-CAM had the best agreement with dermatologists' evaluations. This enhances the promise of Grad-CAM as a useful clinical diagnostic tool. To improve decision-making in skin cancer screening, the results support its inclusion in diagnostic procedures. This study demonstrates the utility of visual interpretation techniques for matching AI results with expert assessments made by humans.

The DeMAL model [50], which takes attention mechanisms into account, is particularly good at resolving difficulties in distinguishing between similar lesion types and provides more accurate and reliable classification. Clinical adoption is greatly hampered by the inability to interpret deep learning models as they become increasingly complex. [67] presented XAI techniques were used to enhance the interpretability and transparency of skin cancer detection models and to improve doctors' decision-making ability by producing AI outputs that are easy to understand, unlike traditional models that often operate as fuzzy boxes. [6] investigated how to enhance the transparency of deep learning models used to diagnose skin cancer by applying XAI techniques. By providing explanations for the model's predictions, the study aims to improve the interpretability of AI-based judgments for medical professionals. Moreover, it increases clinicians' confidence in AI by providing clear, understandable outputs that enable them to make more informed decisions, where traditional models often lack interpretability. The Grad-CAM applied in [68], [61], [69] have enhanced the model transparency and confidence by integrating XAI with deep learning. The work underscores the value of Grad-CAM in building clinician confidence in automated diagnostic systems and the importance of interpretability in AI-based skin cancer detection by focusing on the most important features as in Figure 4 and table 6.

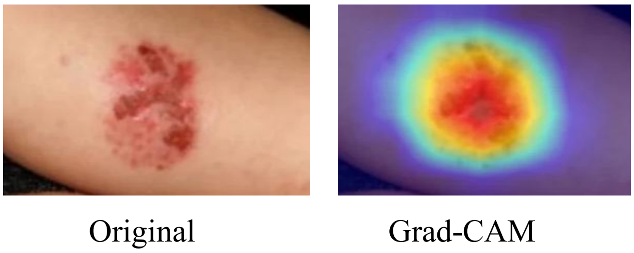

Figure 4. The analysis of thermal and visual imaging [70].

Table 6. Outlines XAI in skin cancer classification.

Ref.	Model	Datasets	#Classess	Accuracy%
[67]	**XAI**	**ISIC**	**2**	**92**
[6]	**CNN & Grad-CAM**	**HAM10000, PH2**	**2**	**N/A**
[69]	**ResNet50v2, EfficientNetB4, DenseNet169**	**MSLD v2.0**	**6**	**99.33, 62.63, 93.94**
[61]	**ViT-GradCAM**	**HAM10000**	**7**	**97.28**
[71]	**U-Net, EfficientNet**	**HAM10000**	**7**	**82**
[65]	**CNN, Grad-CAM and Grad-CAM++**	**HAM10000**	**7**	**81.24**
[66]	**Dl and Grad-CAM++**	**HAM10000, MSK, BCN20000, Derm7pt**	**2**	**81**

3.6 Hybrid Models and Ensemble Techniques

Hybrid models have greatly improved skin lesion classification such as combining CNNs with classic machine learning techniques like support vector machines (SVMs) and k-nearest neighbors (KNN) in [46]. It further enhanced by ensemble learning techniques, which combine predictions from several models to improve accuracy and lessen overfitting [23]. In the same context, [72] improved feature extraction to overcome issues like low contrast in lesion images by employing lightweight attention-guided capsule networks and ResNet50 on the HAM10000 and ISIC 2020 datasets, it showed an impressive accuracy of 98%, indicating its ability to improve automated diagnosis and overcome dataset fluctuations. [73] used an ensemble approach to reduce false positives and increase overall classification accuracy while addressing multi-class melanoma detection. The effectiveness of deep learning and clustering methods that use different CNN architectures and machine learning algorithms to maximize skin cancer classification has also been studied in [74] and [70] which emphasized the importance of model simplicity for clinical integration and the functionality of collective methods in achieving high accuracy. The possibility of facilitating the understanding of complicated patterns by merging the deep learning models with techniques like radiomics in dermoscopy images has been explored by [75] and [76] who were able to achieve an accuracy of 97% and 98.5% respectively. These innovations indicate a significant improvement in the non-invasive diagnosis of melanoma and other skin lesions, pushing the limits of what hybrid models can achieve in medical imaging as shown in table 7.

Table 7. Summary of the hybrid models and ensemble techniques.

Ref.	Model	Datasets	#Classes	Accuracy%
[70]	Max Voting Ensemble	ISIC 2018, HAM10000	7	95.80
[72]	lightweight attention-oriented capsule networks with an active snake model	HAM10000, ISIC 2020	3	98
[73]	DCNN-MSCCA	HAM10000	7	95
[74]	MobileNetV2, InceptionV3	ISIC 2017	3	80.6
[75]	Ensemble(VGG16, Inception-V3, ResNet50)	ISIC 2018, HAM10000	3and 7	97
[76]	Hybrid DL& Radiomics Approach	ISIC 2016-2020	8	98.5

4. Key challenges in deep learning for skin lesion classification

DL has achieved advancements in skin lesion classification. However, various challenges listed below still may limit typical performance.

- The Data Imbalance: rare skin cancer types are often not fully included, making it harder for models to perform well on them.
- Interclass Similarity and Intraclass Variation: skin lesions may look alike across different classes or exhibit significant differences within the same class. Employ advanced models with detailed feature extraction to enhance differentiation between classes.
- Image Quality Variation: variation in lighting, dermoscopy equipment, and imaging parameters will significantly affect model performance. Standardized imaging protocols and preprocessing procedures can reduce variations in image quality.
- Model Generalizability: models tend to be trained on some datasets, which might not be sufficiently representative of all kinds of skin lesions that are encountered in more widespread clinical practice. As such, models must be very generalizable to other populations so that they can be applied validly in the clinical setting.

5. Conclusions

Traditional approaches such as dermoscopy and histopathology are subjective and relied on clinical expertise and this can lead to inconsistent diagnoses. Recently, DL techniques offered more objective, precise ways that help in improving the accuracy and efficiency of classifying skin cancer types especially for early-stage cancers. CNNs and TLs play a vital role in this process by examining dermatoscopic images to identify intricate patterns, helping to minimize diagnostic mistakes between malignant and benign lesions. RNNs bring a dynamic approach by tracking lesion changes over time and improving the early detection of melanoma and other aggressive cancers. To overcome the challenge of limited annotated data, the GANs help in generating realistic synthetic images to improve model performance and generalizability. Despite these advances, challenges remain, such as the lack of interpretability in DL models. Clinicians need clear explanations of how models make decisions, which can be addressed with explainable artificial intelligence (XAI). ViTs take a step further to show the more enhanced results by capturing global image context, which enhances predictions in complex cases where local features alone aren't enough. Looking ahead, DL's integration into telemedicine and mobile healthcare systems holds great promise, improving access to skin cancer detection and potentially reducing mortality, especially in underserved regions. By overcoming current challenges, DL can revolutionize dermatology, making skin cancer detection faster and more reliable.

6. References

1. Tahir, M.; Naeem, A.; Malik, H.; Tanveer, J.; Naqvi, R.A.; Lee, S.W. DSCC_Net: Multi-Classification Deep Learning Models for Diagnosing of Skin Cancer Using Dermoscopic Images. *Cancers* 2023, *15*, doi:10.3390/cancers15072179.
2. Bibi, A.; Khan, M.A.; Javed, M.Y.; Tariq, U.; Kang, B.G.; Nam, Y.; Mostafa, R.R.; Sakr, R.H. Skin Lesion Segmentation and Classification Using Conventional and Deep Learning Based Framework. *Computers, Materials and Continua* 2022, *71*, 2477–2495, doi:10.32604/cmc.2022.018917.
3. SÖNMEZ, A.F.; ÇAKAR, S.; CEREZCİ, F.; KOTAN, M.; DELİBAŞOĞLU, İ.; ÇİT, G. Deep Learning-Based Classification of Dermoscopic Images for Skin Lesions. *Sakarya University Journal of Computer and Information Sciences* 2023, *6*, 114–122, doi:10.35377/saucis...1314638.
4. Rajendran, V.A.; Shanmugam, S. Automated Skin Cancer Detection and Classification Using Cat Swarm Optimization with a Deep Learning Model. *Engineering, Technology & Applied Science Research* 2024, *14*, 12734–12739, doi:10.48084/etasr.6681.
5. Zareen, S.S.; Sun, G.; Kundi, M.; Qadri, S.F.; Qadri, S. Enhancing Skin Cancer Diagnosis with Deep Learning: A Hybrid CNN-RNN Approach. *Computers, Materials and Continua* 2024, *79*, 1497–1519, doi:10.32604/cmc.2024.047418.
6. Hassan, B. Explainable AI for Skin Cancer Diagnosis with Deep Learning Abstract. 2024.
7. Khan, M.A.; Hamza, A.; Shabaz, M.; Kadry, S.; Rubab, S.; Bilal, M.A.; Akbar, M.N.; Kesavan, S.M. Multiclass Skin Lesion Classification Using Deep Learning Networks Optimal Information Fusion. *Discover Applied Sciences* 2024, *6*, doi:10.1007/s42452-024-05998-9.
8. Alipour, N.; Burke, T.; Courtney, J. Skin Type Diversity in Skin Lesion Datasets: A Review. *Current Dermatology Reports* 2024, *13*, 198–210, doi:10.1007/s13671-024-00440-0.
9. He, X.; Wang, Y.; Zhao, S.; Yao, C. Deep Metric Attention Learning for Skin Lesion Classification in Dermoscopy Images. *Complex and Intelligent Systems* 2022, *8*, 1487–1504, doi:10.1007/s40747-021-00587-4.
10. Hasan, S.N. Accurate Deep Learning Algorithms for Skin Lesion Classification. *Ingenierie des Systemes d'Information* 2024, *29*, 1529–1539, doi:10.18280/isi.290426.
11. Öztürk, Ş.; Özkaya, U. Skin Lesion Segmentation with Improved Convolutional Neural Network. *Journal of Digital Imaging* 2020, *33*, 958–970, doi:10.1007/s10278-020-00343-z.
12. Musthafa, M.M.; T R, M.; V, V.K.; Guluwadi, S. Enhanced Skin Cancer Diagnosis Using Optimized CNN Architecture and Checkpoints for Automated Dermatological Lesion Classification. *BMC Medical Imaging* 2024, *24*, 1–21, doi:10.1186/s12880-024-01356-8.
13. Ben Yahia, K.; Saadaoui, E. Morphological Variability of the Acorns of Three Species of Oaks from North-West Tunisia. 2023.
14. Sikandar, S.; Mahum, R.; Ragab, A.E.; Yayilgan, S.Y.; Shaikh, S. SCDet: A Robust Approach for the Detection of Skin Lesions. *Diagnostics* 2023, *13*, doi:10.3390/diagnostics13111824.
15. Rotemberg, V.; Kurtansky, N.; Betz-Stablein, B.; Caffery, L.; Chousakos, E.; Codella, N.; Combalia, M.; Dusza, S.; Guitera, P.; Gutman, D.; et al. A Patient-Centric Dataset of Images and Metadata for Identifying Melanomas Using Clinical Context. *Scientific Data* 2021, *8*, 1–9, doi:10.1038/s41597-021-00815-z.
16. Sarwar, N.; Irshad, A.; Naith, Q.H.; D Alsufiani, K.; Almalki, F.A. Skin Lesion Segmentation Using Deep Learning Algorithm with Ant Colony Optimization. *BMC medical informatics and decision making* 2024, *24*, 265, doi:10.1186/s12911-024-02686-x.
17. Sikandar, S.; Mahum, R.; Ragab, A.E.; Yayilgan, S.Y.; Shaikh, S. SCDet: A Robust Approach for the Detection of Skin Lesions. *Diagnostics* 2023, *13*, doi:10.3390/diagnostics13111824.
18. Ali, Z.; Naz, S.; Zaffar, H.; Choi, J.; Kim, Y. An IoMT-Based Melanoma Lesion Segmentation Using Conditional Generative Adversarial Networks. *Sensors* 2023, *23*, doi:10.3390/s23073548.
19. Hosny, K.M.; Kassem, M.A.; Foaud, M.M. Skin Melanoma Classification Using ROI and Data Augmentation with Deep Convolutional Neural Networks. *Multimedia Tools and Applications* 2020, *79*, 24029–24055, doi:10.1007/s11042-020-09067-2.
20. Dihan, F.J.; Murad, S.A.; Jafar, A.; Muzahid, M.; Aslam Uddin, K.M.; Alenazi, M.J.F.; Kumar Bairagi, A.; Biswas, S. MpoxSLDNet: A Novel CNN Model for Detecting Monkeypox Lesions and Performance Comparison with Pre-Trained Models. 2024, 1–13.
21. Yang, G.; Luo, S.; Greer, P. Advancements in Skin Cancer Classification: A Review of Machine Learning Techniques in Clinical Image Analysis. *Multimedia Tools and Applications* 2024, doi:10.1007/s11042-024-19298-2.
22. Samrin, S.; Nadaf, S.; Matthew-ibhafidon, D.O.; Srivastava, N. Understanding Skin Cancer: A Review. *International Research Journal of Modernization in Engineering Technology and Science* 2024, doi:10.56726/irjmets60147.

23. Hsu, S.T.; Su, Y.J.; Hung, C.H.; Chen, M.J.; Lu, C.H.; Kuo, C.E. Automatic Ovarian Tumors Recognition System Based on Ensemble Convolutional Neural Network with Ultrasound Imaging. *BMC Medical Informatics and Decision Making* 2022, *22*, 1–13, doi:10.1186/s12911-022-02047-6.
24. Azeem, M.; Kiani, K.; Mansouri, T.; Topping, N. SkinLesNet: Classification of Skin Lesions and Detection of Melanoma Cancer Using a Novel Multi-Layer Deep Convolutional Neural Network. *Cancers* 2024, *16*, 1–15, doi:10.3390/cancers16010108.
25. Chunhapran, O.; Maliyeam, M.; Quirchmayr, G. Monkeypox Lesion and Rash Stage Classification Using Deep Learning Technique. *Lecture Notes in Networks and Systems* 2024, *973 LNNS*, 141–149, doi:10.1007/978-3-031-58561-6_14.
26. Hoang, L.; Lee, S.H.; Lee, E.J.; Kwon, K.R. Multiclass Skin Lesion Classification Using a Novel Lightweight Deep Learning Framework for Smart Healthcare. *Applied Sciences (Switzerland)* 2022, *12*, doi:10.3390/app12052677.
27. Chen, S. Exploring the Application of Machine Learning for Skin Cancer Image Identification. 2024, *11*, doi:10.54254/2977-3903/11/2024108.
28. Khudzari, Z.M. Biomedical System Design. 2024.
29. Abedini, M. Skin Cancer Classification by Leveraging Segment Anything Model for Semantic Segmentation of Skin Lesion. *Ijarcce* 2024, *13*, doi:10.17148/ijarcce.2024.13835.
30. Al-Rakhami, M.S.; AlQahtani, S.A.; Alawwad, A. Effective Skin Cancer Diagnosis Through Federated Learning and Deep Convolutional Neural Networks. *Applied Artificial Intelligence* 2024, *38*, 1–27, doi:10.1080/08839514.2024.2364145.
31. Vidyapeetham, A.V. Unveiling Dermatological Threats : Deep Learning-Based Skin Cancer Classification from Lesion Images. 2024, doi:10.6084/m9.doione.IJNRD2403634.
32. Mir, A.N.; Nissar, I.; Rizvi, D.R.; Kumar, A. LesNet: An Automated Skin Lesion Deep Convolutional Neural Network Classifier through Augmentation and Transfer Learning. *Procedia Computer Science* 2024, *235*, 112–121, doi:10.1016/j.procs.2024.04.014.
33. ORNEK, H.K.; YILMAZ, B.; YASIN, E.; KOKLU, M. Deep Learning-Based Classification of Skin Lesion Dermoscopic Images for Melanoma Diagnosis. *Intelligent Methods in Engineering Sciences* 2024, doi:10.58190/imiens.2024.101.
34. Vasanthakumari, P.; Romano, R.A.; Rosa, R.G.T.; Salvio, A.G.; Yakovlev, V.; Kurachi, C.; Hirshburg, J.M.; Jo, J.A. Pixel-Level Classification of Pigmented Skin Cancer Lesions Using Multispectral Autofluorescence Lifetime Dermoscopy Imaging. *Biomedical Optics Express* 2024, *15*, 4557, doi:10.1364/boe.523831.
35. Zhang, L.; Xiao, X.; Wen, J.; Li, H. MDKLoss: Medicine Domain Knowledge Loss for Skin Lesion Recognition. *Mathematical Biosciences and Engineering* 2024, *21*, 2671–2690, doi:10.3934/mbe.2024118.
36. Hameed, M.; Zameer, A.; Zahoor Raja, M.A. A Comprehensive Systematic Review: Advancements in Skin Cancer Classification and Segmentation Using the ISIC Dataset. *CMES - Computer Modeling in Engineering and Sciences* 2024, *140*, 2131–2164, doi:10.32604/cmes.2024.050124.
37. Wortsman, X. Ultrasound in Skin Cancer: Why, How, and When to Use It? *Cancers* 2024, *16*, doi:10.3390/cancers16193301.
38. Ayana, G.; Dese, K.; Abagaro, A.M.; Jeong, K.C.; Yoon, S. Do; Choe, S.W. *Multistage Transfer Learning for Medical Images*; Springer Netherlands, 2024; Vol. 57; ISBN 0123456789.
39. Ashraf, R.; Afzal, S.; Rehman, A.U.; Gul, S.; Baber, J.; Bakhtyar, M.; Mehmood, I.; Song, O.Y.; Maqsood, M. Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection. *IEEE Access* 2020, *8*, 147858–147871, doi:10.1109/ACCESS.2020.3014701.
40. Profile, S.E.E. Classification of Skin Diseases with Different Deep Learning Models and Comparison of the Performances of the Models Classification of Skin Diseases with Different Deep Learning Models and Comparison of the Performances of the Models Farklı Derin Öğrenme . 2024, doi:10.46810/tdfd.1502471.
41. Chatterjee, S.; Gil, J.M.; Byun, Y.C. Early Detection of Multiclass Skin Lesions Using Transfer Learning-Based IncepX-Ensemble Model. *IEEE Access* 2024, *12*, 113677–113693, doi:10.1109/ACCESS.2024.3432904.
42. Primiero, C.A.; Betz-Stablein, B.; Ascott, N.; D'Alessandro, B.; Gaborit, S.; Fricker, P.; Goldsteen, A.; González-Villà, S.; Lee, K.; Nazari, S.; et al. A Protocol for Annotation of Total Body Photography for Machine Learning to Analyze Skin Phenotype and Lesion Classification. *Frontiers in Medicine* 2024, *11*, 1–14, doi:10.3389/fmed.2024.1380984.
43. Ramamurthy, K.; Thayumanaswamy, I.; Radhakrishnan, M.; Won, D.; Lingaswamy, S. Integration of Localized, Contextual, and Hierarchical Features in Deep Learning for Improved Skin Lesion Classification. *Diagnostics* 2024, *14*, doi:10.3390/diagnostics14131338.
44. Harahap, M.; Husein, A.M.; Kwok, S.C.; Wizley, V.; Leonardi, J.; Ong, D.K.; Ginting, D.; Silitonga, B.A. Skin Cancer Classification Using EfficientNet Architecture. *Bulletin of Electrical Engineering and Informatics* 2024, *13*, 2716–2728, doi:10.11591/eei.v13i4.7159.

45. Ali, M.U.; Khalid, M.; Alshanbari, H.; Zafar, A.; Lee, S.W. Enhancing Skin Lesion Detection: A Multistage Multiclass Convolutional Neural Network-Based Framework. *Bioengineering* 2023, *10*, 1–16, doi:10.3390/bioengineering10121430.
46. Khan, A.H.; Awang Iskandar, D.N.F.; Al-Asad, J.F.; Mewada, H.; Sherazi, M.A. Ensemble Learning of Deep Learning and Traditional Machine Learning Approaches for Skin Lesion Segmentation and Classification. *Concurrency and Computation: Practice and Experience* 2022, *34*, doi:10.1002/cpe.6907.
47. Akram, A.; Rashid, J.; Jaffar, M.A.; Faheem, M.; Amin, R. ul Segmentation and Classification of Skin Lesions Using Hybrid Deep Learning Method in the Internet of Medical Things. *Skin Research and Technology* 2023, *29*, doi:10.1111/srt.13524.
48. Deng, X.; Yin, Q.; Guo, P. Efficient Structural Pseudoinverse Learning-Based Hierarchical Representation Learning for Skin Lesion Classification. *Complex and Intelligent Systems* 2022, *8*, 1445–1457, doi:10.1007/s40747-021-00588-3.
49. Hussain, M.; Khan, M.A.; Damaševičius, R.; Alasiry, A.; Marzougui, M.; Alhaisoni, M.; Masood, A. SkinNet-INIO: Multiclass Skin Lesion Localization and Classification Using Fusion-Assisted Deep Neural Networks and Improved Nature-Inspired Optimization Algorithm. *Diagnostics* 2023, *13*, doi:10.3390/diagnostics13182869.
50. Goyal, M.; Knackstedt, T.; Yan, S.; Hassanpour, S. Artificial Intelligence-Based Image Classification Methods for Diagnosis of Skin Cancer: Challenges and Opportunities. *Computers in Biology and Medicine* 2020, *127*, 104065, doi:10.1016/j.compbiomed.2020.104065.
51. Zola, F.; Segurola-Gil, L.; Bruse, J.L.; Galar, M.; Orduna-Urrutia, R. Attacking Bitcoin Anonymity: Generative Adversarial Networks for Improving Bitcoin Entity Classification. *Applied Intelligence* 2022, *52*, 17289–17314, doi:10.1007/s10489-022-03378-7.
52. Navidan, H.; Moshiri, P.F.; Nabati, M.; Shahbazian, R.; Ghorashi, S.A.; Shah-Mansouri, V.; Windridge, D. Generative Adversarial Networks (GANs) in Networking: A Comprehensive Survey & Evaluation. *Computer Networks* 2021, *194*, doi:10.1016/j.comnet.2021.108149.
53. Mutepfe, F.; Kalejahi, B.K.; Meshgini, S.; Danishvar, S. Generative Adversarial Network Image Synthesis Method for Skin Lesion Generation and Classification. *Journal of Medical Signals and Sensors* 2021, *11*, 237–252, doi:10.4103/jmss.JMSS_53_20.
54. Ben Yahia, K.; Saadaoui, E. Morphological Variability of the Acorns of Three Species of Oaks from North-West Tunisia. 2023.
55. Su, Q.; Hamed, H.N.A.; Isa, M.A.; Hao, X.; Dai, X. A GAN-Based Data Augmentation Method for Imbalanced Multi-Class Skin Lesion Classification. *IEEE Access* 2024, *12*, 16498–16513, doi:10.1109/ACCESS.2024.3360215.
56. Nyemeesha, V. SCDC-Net: Skin Cancer Detection and Classification Using Deep Q Neural Network with Hybrid Features. *International Journal on Recent and Innovation Trends in Computing and Communication* 2022, *10*, 70–84, doi:10.17762/ijritcc.v10i7.5573.
57. Meedeniya, D.; De Silva, S.; Gamage, L.; Isuranga, U. Skin Cancer Identification Utilizing Deep Learning: A Survey. *IET Image Processing* 2024, 1–19, doi:10.1049/ipr2.13219.
58. Debelee, T.G. Skin Lesion Classification and Detection Using Machine Learning Techniques: A Systematic Review. *Diagnostics* 2023, *13*, doi:10.3390/diagnostics13193147.
59. Himel, G.M.S.; Islam, M.M.; Al-Aff, K.A.; Karim, S.I.; Sikder, M.K.U. Skin Cancer Segmentation and Classification Using Vision Transformer for Automatic Analysis in Dermatoscopy-Based Noninvasive Digital System. *International Journal of Biomedical Imaging* 2024, *2024*, doi:10.1155/2024/3022192.
60. Rani, A.; Khalil, A.; Shah, Y.A.; Jr, I. Deep Learning-Based Skin Lesion Segmentation and Classification. 2024.
61. Shafiq, M.; Aggarwal, K.; Jayachandran, J.; Srinivasan, G.; Boddu, R.; Alemayehu, A. A Novel Skin Lesion Prediction and Classification Technique: ViT-GradCAM. *Skin Research and Technology* 2024, *30*, 1–12, doi:10.1111/srt.70040.
62. Gallazzi, M.; Biavaschi, S.; Bulgheroni, A.; Gatti, T.M.; Corchs, S.; Gallo, I. A Large Dataset to Enhance Skin Cancer Classification With Transformer-Based Deep Neural Networks. *IEEE Access* 2024, *12*, 109544–109559, doi:10.1109/ACCESS.2024.3439365.
63. Remya, S.; Anjali, T.; Sugumaran, V. A Novel Transfer Learning Framework for Multimodal Skin Lesion Analysis. *IEEE Access* 2024, *12*, 50738–50754, doi:10.1109/ACCESS.2024.3385340.
64. Son, H.M.; Jeon, W.; Kim, J.; Heo, C.Y.; Yoon, H.J.; Park, J.U.; Chung, T.M. AI-Based Localization and Classification of Skin Disease with Erythema. *Scientific Reports* 2021, *11*, 1–15, doi:10.1038/s41598-021-84593-z.
65. Mridha, K.; Uddin, M.M.; Shin, J.; Khadka, S.; Mridha, M.F. An Interpretable Skin Cancer Classification Using Optimized Convolutional Neural Network for a Smart Healthcare System. *IEEE Access* 2023, *11*, 41003–41018, doi:10.1109/ACCESS.2023.3269694.

66. Giavina-Bianchi, M.; Vitor, W.G.; Fornasiero de Paiva, V.; Okita, A.L.; Sousa, R.M.; Machado, B. Explainability Agreement between Dermatologists and Five Visual Explanations Techniques in Deep Neural Networks for Melanoma AI Classification. *Frontiers in Medicine* 2023, *10*, doi:10.3389/fmed.2023.1241484.
67. Azlaan, H.; Oluwaseyi, J. Explainable AI (XAI) for Skin Cancer Detection. 2024.
68. Kassem, M.A.; Hosny, K.M.; Damaševičius, R.; Eltoukhy, M.M. Machine Learning and Deep Learning Methods for Skin Lesion Classification and Diagnosis: A Systematic Review. *Diagnostics* 2021, *11*, 1–29, doi:10.3390/diagnostics11081390.
69. Idroes, G.M.; Noviandy, T.R.; Emran, T. Bin; Idroes, R. Explainable Deep Learning Approach for Mpox Skin Lesion Detection with Explainable Deep Learning Approach for Mpox Skin Lesion Detection with Grad-CAM. 2024, doi:10.60084/hjas.v2i2.216.
70. Natha, P.; RajaRajeswari, P. Advancing Skin Cancer Prediction Using Ensemble Models. *Computers* 2024, *13*, doi:10.3390/computers13070157.
71. Son, H.M.; Jeon, W.; Kim, J.; Heo, C.Y.; Yoon, H.J.; Park, J.U.; Chung, T.M. AI-Based Localization and Classification of Skin Disease with Erythema. *Scientific Reports* 2021, *11*, 1–14, doi:10.1038/s41598-021-84593-z.
72. Behara, K.; Bhero, E.; Agee, J.T. An Improved Skin Lesion Classification Using a Hybrid Approach with Active Contour Snake Model and Lightweight Attention-Guided Capsule Networks. *Diagnostics* 2024, *14*, doi:10.3390/diagnostics14060636.
73. Hassan, B. Ensemble Learning for Multi-Class Skin Cancer Detection. 2024.
74. Gamil, S.; Zeng, F.; Alrifaey, M.; Asim, M.; Ahmad, N. An Efficient AdaBoost Algorithm for Enhancing Skin Cancer Detection and Classification. *Algorithms* 2024, *17*, doi:10.3390/a17080353.
75. Thwin, S.M. Applied Sciences. *Early Writings on India* 2018, 124–134, doi:10.4324/9781315232140-14.
76. Wang, Z.; Wang, C.; Peng, L.; Lin, K.; Xue, Y.; Chen, X.; Bao, L.; Liu, C.; Zhang, J.; Xie, Y. Radiomic and Deep Learning Analysis of Dermoscopic Images for Skin Lesion Pattern Decoding. *Scientific Reports* 2024, *14*, 1–14, doi:10.1038/s41598-024-70231-x.