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**| RESEARCH ARTICLE**

# Deep Learning–Based Skin Cancer Diagnosis in the United States: Advances, Challenges, and Clinical Translation

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## | ABSTRACT
Skin cancer represents one of the most common and potentially fatal malignancies in the United States. Where timely and accurate diagnosis is critical for reducing mortality and healthcare burden. Current diagnostic practices, including visual examination and dermoscopy. This rely heavily on clinician expertise and are subject to inter-observer variability, particularly in early-stage disease. In recent years, deep learning has emerged as a promising tool for automating skin cancer detection from dermoscopic images. With offering improved diagnostic accuracy and scalability. This article provides a comprehensive analysis of deep learning-based approaches for skin cancer classification, with a focus on convolutional neural network architectures, commonly used datasets, and performance evaluation metrics relevant to U.S. clinical settings. Key challenges, including dataset imbalance, limited representation of diverse skin tones, overfitting on small cohorts, and high computational demands, are critically examined. Additionally, the study discusses emerging trends toward lightweight and deployable models suited for real-time clinical workflows and mobile health applications within the United States healthcare system. The findings aim to support the development of robust, generalizable, and clinically translatable deep learning solutions for skin cancer diagnosis.

## | KEYWORDS

Skin cancer detection, Deep learning, Convolutional neural networks, Dermoscopic images, Medical image classification, Dataset bias, Lightweight models, Computer-aided diagnosis.

**| ARTICLE INFORMATION**

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## 1. Introduction

Skin cancer is one of the most common and potentially fatal forms of cancer worldwide and represents a significant public health burden in the United States, arising from the uncontrolled proliferation of abnormal skin cells primarily caused by excessive exposure to ultraviolet (UV) radiation [1]. According to global cancer statistics, including trends observed in the United States, the incidence of skin cancer has increased steadily over the past decades, making it a major concern for healthcare systems and preventive medicine [2]. Among various types, melanoma is the most aggressive and life-threatening form of skin cancer in the United States due to its high metastatic potential; however, early-stage melanoma has a significantly higher survival rate when detected and treated promptly [3]. Conventional skin cancer diagnosis in the United States relies heavily on visual inspection and dermoscopic examination performed by experienced dermatologists. Although dermoscopy improves diagnostic accuracy compared to naked-eye examination, the process remains subjective and dependent on clinical expertise, leading to inter-observer variability and diagnostic inconsistency across clinical settings [4,5]. Moreover, early-stage lesions often lack distinct visual characteristics, making accurate diagnosis challenging even for trained professionals in routine U.S. clinical practice [6]. To overcome these limitations, computer-aided diagnosis (CAD) systems have been introduced to assist clinicians in the United States with skin cancer detection and classification [7]. Traditional CAD approaches typically involve multiple stages, including image preprocessing, lesion segmentation, handcrafted feature extraction, and classification [8].

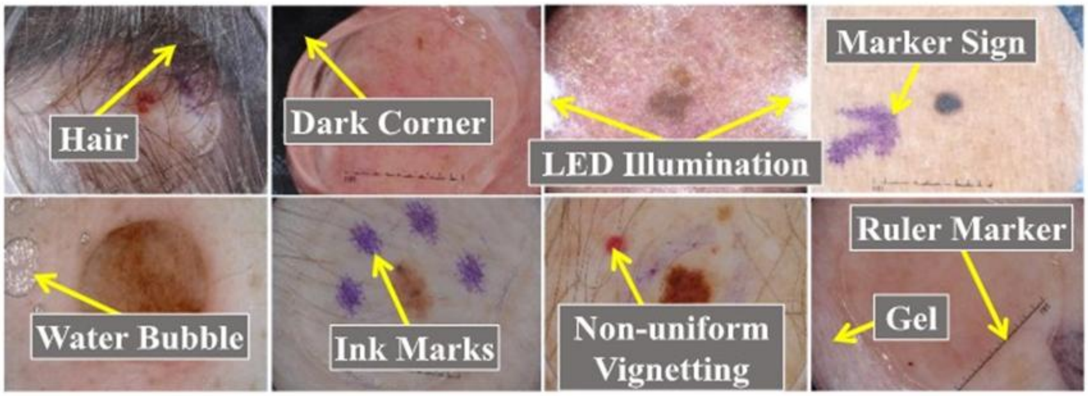


**Figure 1.** Skin cancers with artifacts adapted from

However, the performance of these methods is highly sensitive to feature design and image quality, limiting their robustness and scalability. Recent advances in deep learning, particularly convolutional neural networks (CNNs), have revolutionized medical image analysis by enabling automatic feature learning directly from raw images [9,10]. Deep learning–based models have demonstrated remarkable performance in skin cancer classification, often matching or exceeding dermatologist-level accuracy under controlled conditions [11]. Popular architectures such as AlexNet, VGG, ResNet, DenseNet, and MobileNet have been widely adopted for dermoscopic image analysis due to their strong representation learning capabilities [12–14]. Despite promising results, several challenges hinder the real-world deployment of deep learning models for skin cancer diagnosis. These include limited availability of large and diverse annotated datasets, class imbalance, skin-tone bias, overfitting on small datasets, and high computational complexity of deep architectures [15–17]. Furthermore, many existing models lack generalizability across datasets collected from different populations and imaging conditions, raising concerns about their clinical reliability [18-21]. Motivated by these challenges, this study aims to provide a comprehensive and critical analysis of deep learning–based approaches for skin cancer detection and classification. The focus is placed on commonly used model architectures, datasets, performance metrics, and practical limitations, while highlighting emerging trends toward lightweight and deployable solutions for real-time clinical and mobile healthcare applications.

## 2. Convolutional Neural Networks for Image Classification

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed to process grid-structured data such as images. Owing to their ability to automatically learn hierarchical feature representations, CNNs have become the dominant approach for image recognition, classification, segmentation, and object detection tasks. In medical image analysis, CNNs eliminate the need for handcrafted feature extraction by directly learning discriminative patterns from raw input images.

A typical CNN consists of multiple stacked layers that progressively extract low-level to high-level features. Early layers capture simple visual cues such as edges, textures, and color variations, while deeper layers learn complex semantic representations relevant to the target classification task. This hierarchical learning process makes CNNs particularly effective for analyzing dermoscopic images, where subtle visual differences can indicate malignant skin lesions.

The fundamental building blocks of CNNs include convolutional layers, activation functions, and pooling layers. Convolutional layers apply learnable filters to input images to extract spatial features. Activation functions, such as the Rectified Linear Unit (ReLU), introduce nonlinearity and accelerate training by suppressing negative activations. Pooling layers reduce spatial dimensionality, decrease computational cost, and improve robustness to minor spatial variations. The final classification is performed using fully connected layers followed by a softmax or sigmoid function, depending on the classification task.

### *2.1. Widely Used CNN Architectures in Image Classification*

Several CNN architectures have been extensively adopted for skin cancer detection due to their strong feature extraction capabilities. This section summarizes the most influential architectures that serve as the foundation for many deep-learning-based skin lesion classification systems.

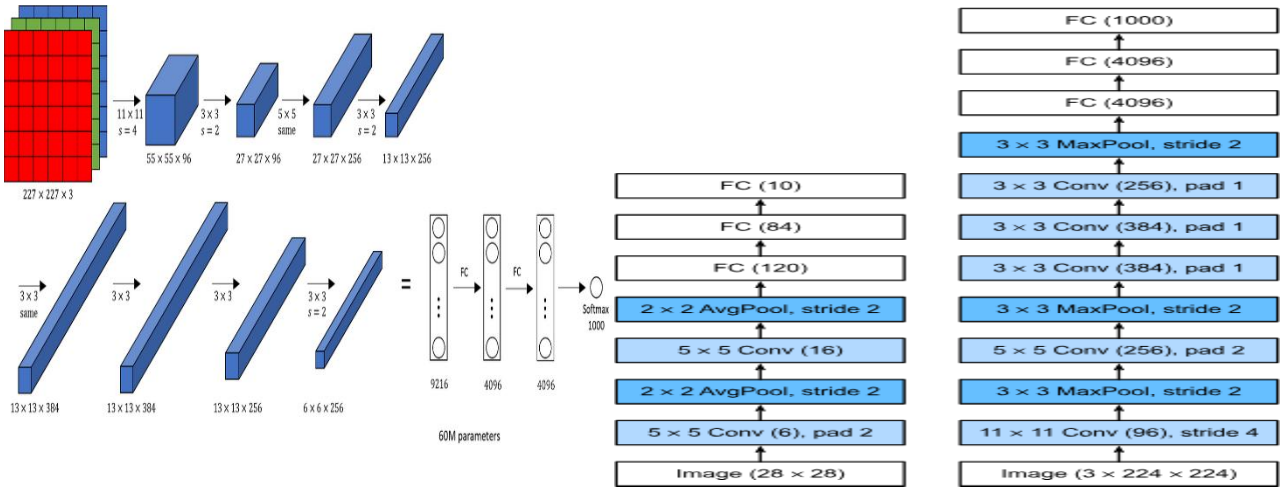


**Figure 2.** Architecture of the AlexNet convolutional neural network.

### *2.2. AlexNet*

AlexNet is one of the earliest deep CNN architectures that demonstrated the effectiveness of deep learning for large-scale image classification. It consists of five convolutional layers followed by three fully connected layers and employs ReLU activation to accelerate convergence. Dropout regularization is applied to mitigate overfitting. Despite its relatively large number of parameters, AlexNet introduced key design principles that influenced later architectures, making it a baseline model for many medical imaging applications.

### *2.3. VGG Network*

The VGG architecture emphasizes simplicity and uniformity by using small $3 \times 3$convolutional filters throughout the network. VGG-16 and VGG-19 are the most commonly used variants, differing in depth. The increased depth enables VGG models to learn highly discriminative features, leading to strong performance in image classification tasks. However, VGG networks contain a large number of parameters, which results in high memory consumption and computational cost. Despite this limitation, VGG models remain popular for transfer learning in skin cancer classification.

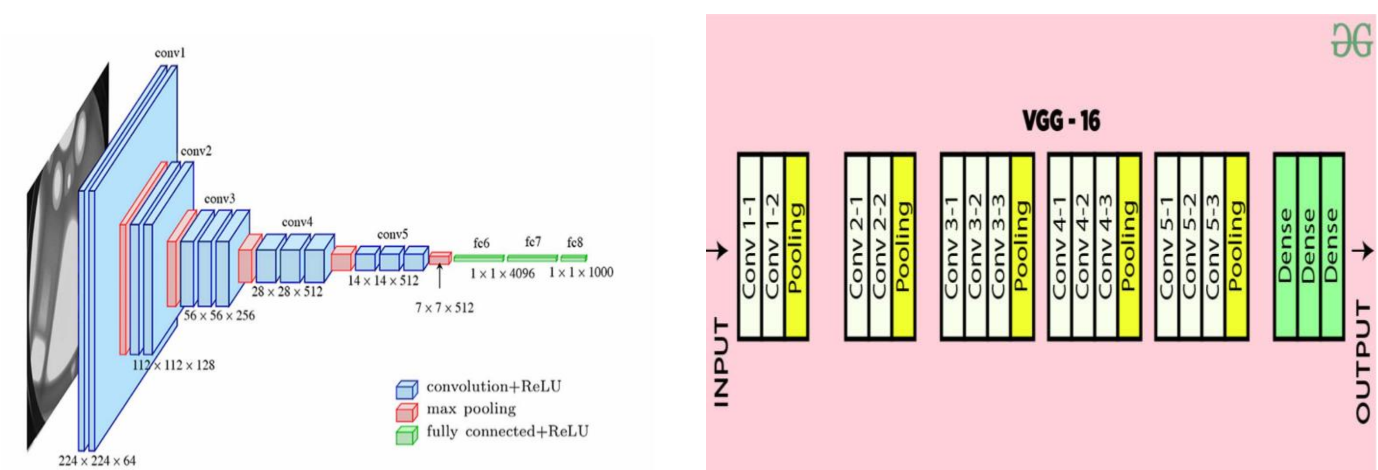


**Figure 3.** Structure of the VGG-16 convolutional neural network.

### 2.4. ResNet

As CNN depth increases, training becomes challenging due to vanishing and exploding gradient problems. Residual Networks (ResNet) address this issue by introducing residual connections, also known as skip connections, which allow gradients to flow directly across layers. By learning residual mappings instead of direct mappings, ResNet enables the training of very deep networks without performance degradation. This design significantly improves classification accuracy and model stability, making ResNet one of the most widely used architectures in skin cancer analysis.

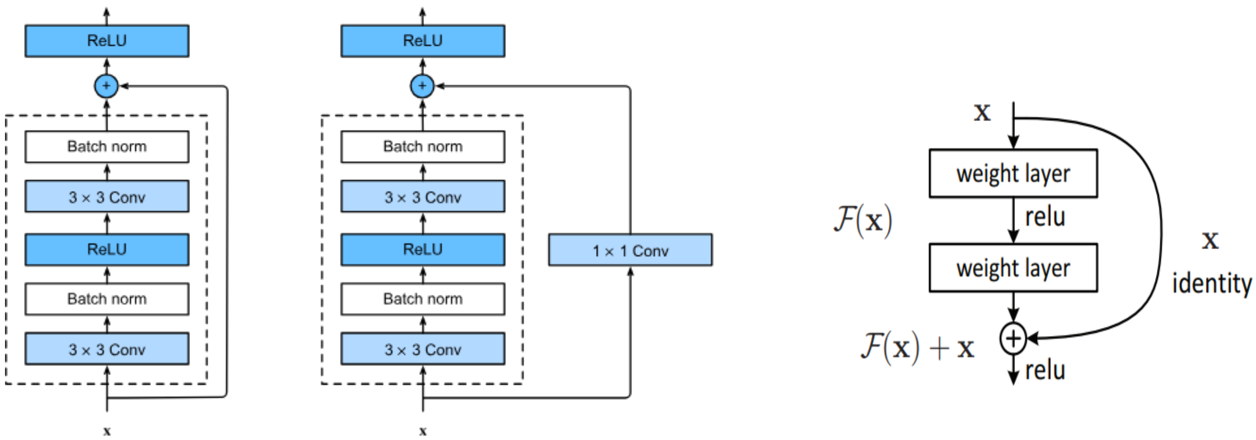


**Figure 4.** Residual learning framework used in ResNet architecture.

### 2.5. DenseNet

DenseNet introduces dense connectivity, where each layer receives feature maps from all preceding layers. This architecture encourages feature reuse, strengthens gradient propagation, and reduces the number of parameters required compared to traditional deep CNNs. DenseNet models have demonstrated strong performance in medical image classification tasks, particularly when training data is limited. However, dense connections increase memory usage, which may limit deployment in resource-constrained environments.

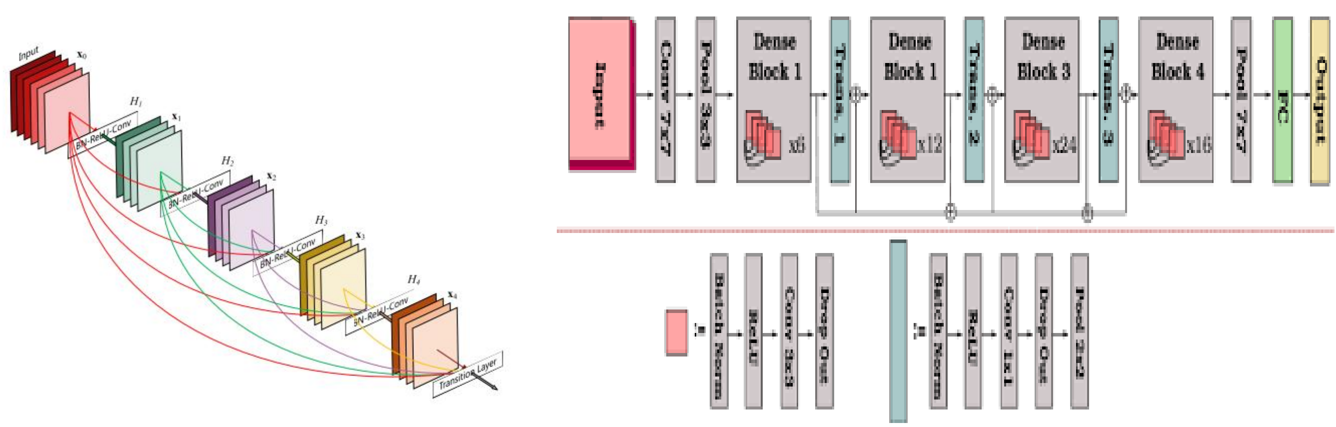


**Figure 5.** Dense connectivity pattern in DenseNet architecture.

### 2.6. MobileNet

MobileNet is a lightweight CNN architecture specifically designed for mobile and embedded applications. It replaces standard convolutions with depthwise separable convolutions, which significantly reduce the number of parameters and computational cost. This efficiency makes MobileNet highly suitable for real-time skin cancer detection on mobile devices and edge-based healthcare systems, where computational resources are limited.

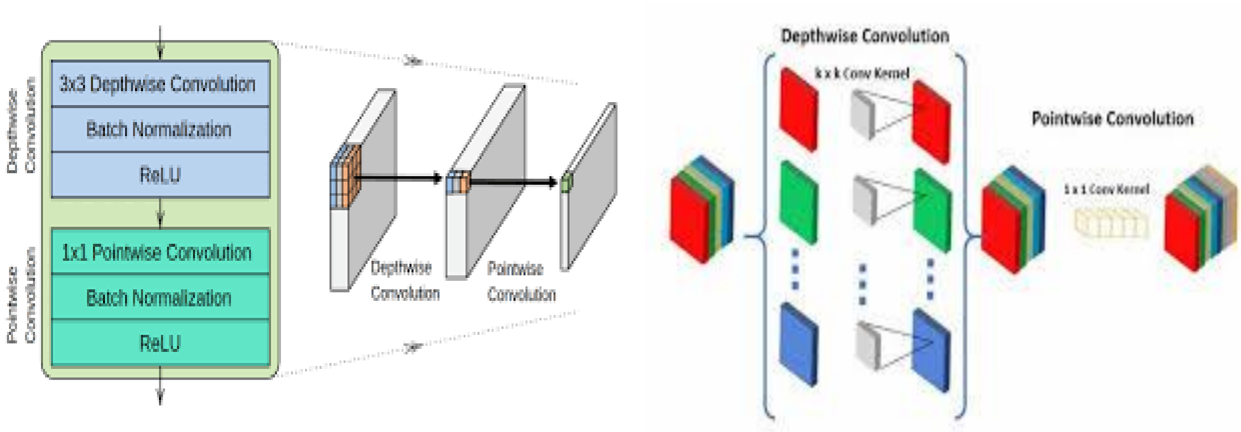


**Figure 6.** Comparison between standard convolution and depthwise separable convolution.

**Table 1.** Comparison of commonly used CNN architectures for skin cancer classification.

| Architecture | Key Characteristics | Advantages | Limitations |
|---|---|---|---|
| AlexNet | Shallow CNN with large filters | Simple, effective baseline | High parameter count |
| VGG-16 / VGG-19 | Deep network with uniform filters | High feature representation | Computationally expensive |
| ResNet | Residual learning with skip connections | Enables very deep networks | Increased complexity |
| DenseNet | Dense feature reuse | Efficient gradient flow | High memory usage |
| MobileNet | Depthwise separable convolutions | Lightweight, fast | Slight accuracy trade-off |

## 3. Deep-Learning-Based Skin Cancer Classification

Deep learning has emerged as a powerful paradigm for automated skin cancer classification due to its ability to learn discriminative features directly from dermoscopic images. Unlike traditional machine-learning approaches that rely on handcrafted features, deep-learning-based models integrate feature extraction and classification into a unified framework, resulting in improved robustness and accuracy.

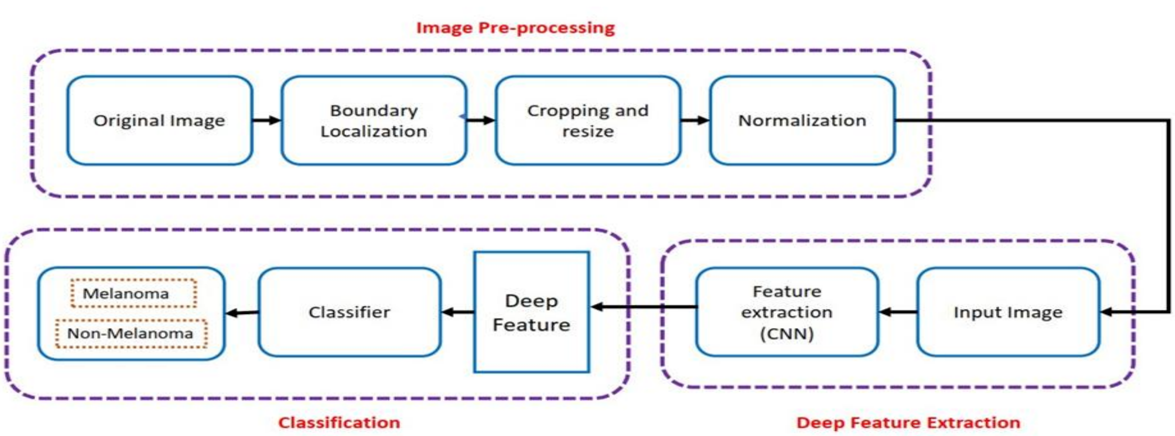


**Figure 7.** Automated classification network proposed in research

### *3.1. Classification Framework*

A typical deep-learning-based skin cancer classification pipeline consists of image preprocessing, feature learning using convolutional neural networks, and final lesion classification. Dermoscopic images are first normalized and resized to meet network input requirements. In some approaches, lesion segmentation is applied as a preprocessing step to isolate the region of interest and suppress background noise, thereby improving classification performance.

CNN-based models automatically learn hierarchical representations of skin lesions. Lower layers capture basic visual patterns such as edges and color gradients, while deeper layers learn high-level semantic features related to lesion shape, texture, and structural irregularities. These learned features are then passed to fully connected layers or global pooling layers for final classification into benign or malignant categories, or into multiple lesion classes.

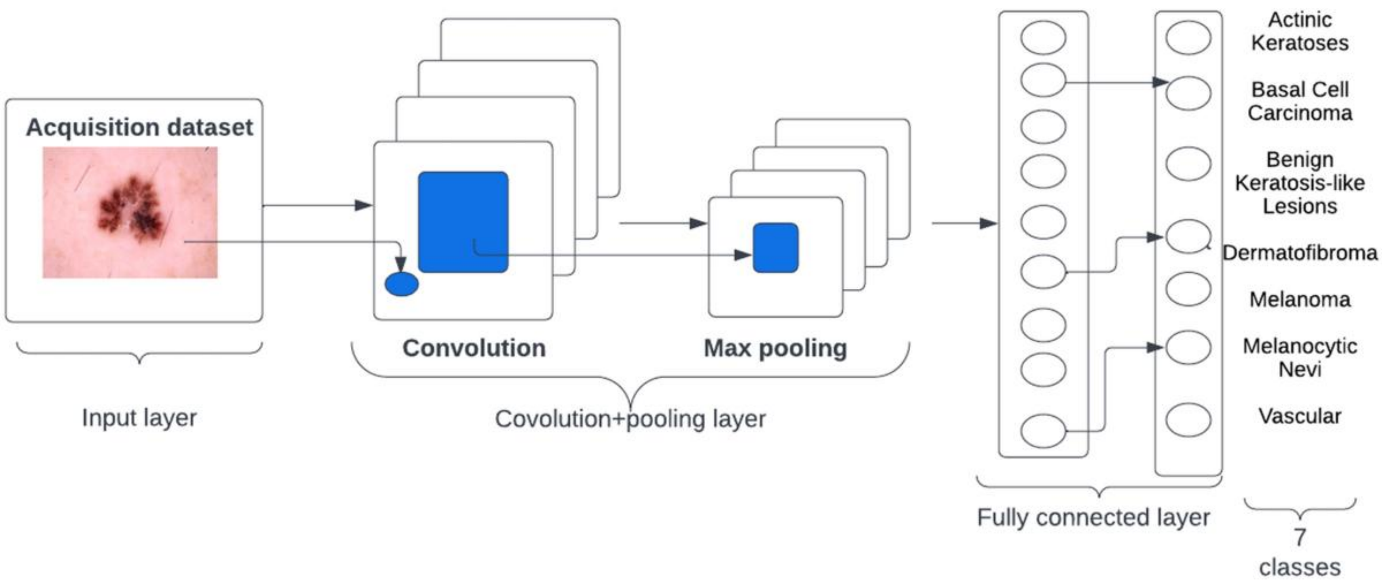


**Figure 8.** Deep-Learning-Based Skin Cancer Classification Framework

### *3.2. Transfer Learning and Fine-Tuning*

Due to the limited availability of large, well-annotated medical image datasets, transfer learning has become a dominant strategy in skin cancer classification. In this approach, CNN models pre-trained on large-scale natural image datasets are fine-tuned using dermoscopic images. Transfer learning enables faster convergence, reduces overfitting, and improves generalization, particularly when training data is scarce. Fine-tuning strategies vary across studies. Some approaches freeze early convolutional layers and retrain only the classification head, while others fine-tune deeper layers to adapt the learned representations to the skin lesion domain. The choice of strategy depends on dataset size, class balance, and computational constraints.

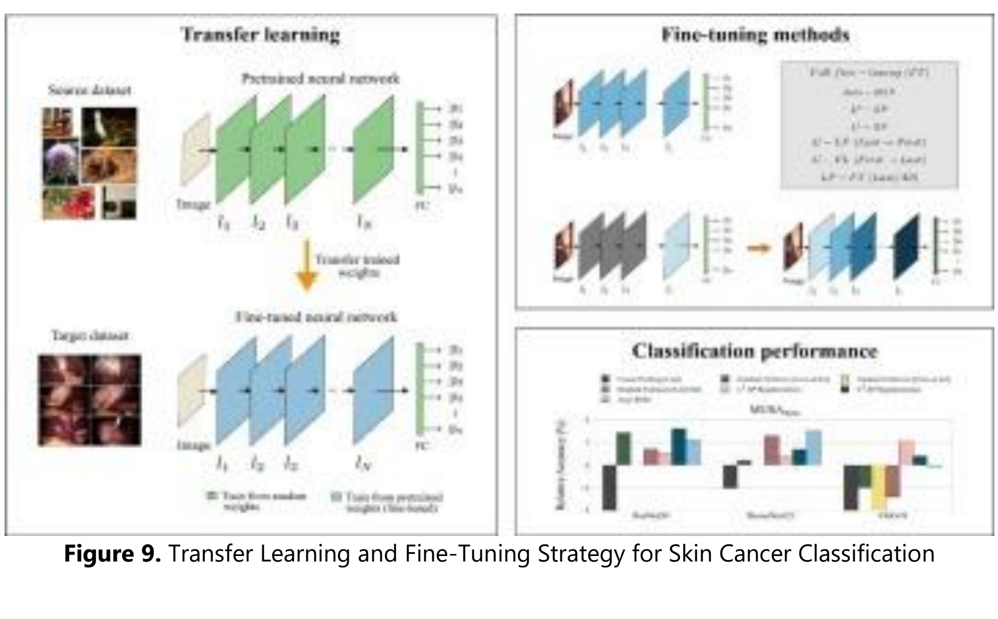


**Figure 9.** Transfer Learning and Fine-Tuning Strategy for Skin Cancer Classification

### *33. Binary and Multi-Class Classification*

Deep-learning-based skin cancer classification is commonly formulated as either a binary or multi-class problem. Binary classification focuses on distinguishing malignant from benign lesions, which is clinically relevant for early melanoma screening. Multi-class classification aims to differentiate between multiple lesion types such as melanoma, basal cell carcinoma, squamous cell carcinoma, and benign nevi. While binary classification often achieves higher accuracy, multi-class classification better reflects real-world clinical scenarios but remains more challenging due to class imbalance and inter-class similarity. Deep models trained for multi-class tasks require careful dataset preparation, balanced sampling, and robust evaluation metrics to ensure reliable performance.

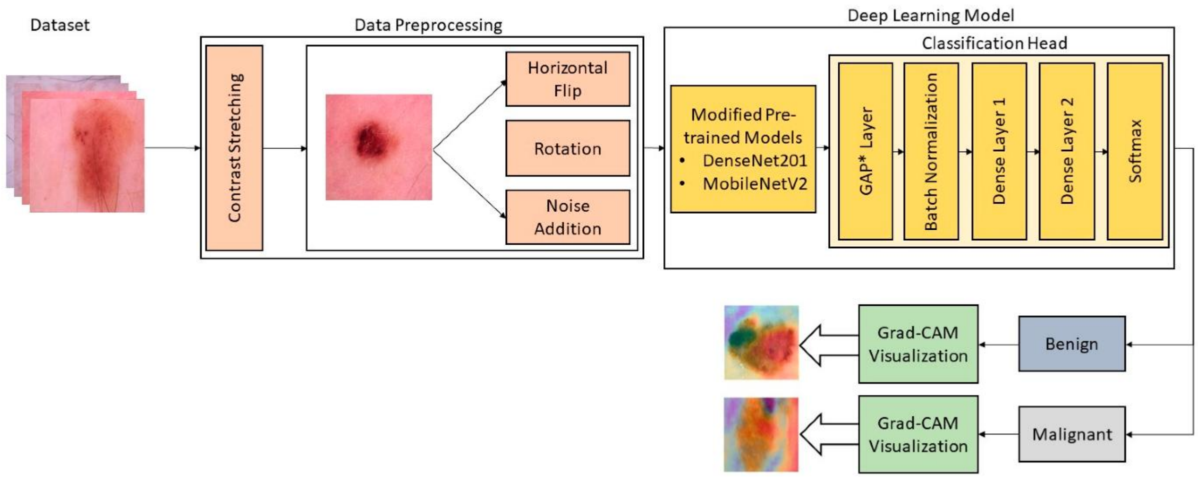


**Figure 10.** Binary and Multi-Class Classification Strategies for Skin Cancer Detection

### *3.4. Performance Evaluation*

The effectiveness of deep-learning-based classifiers is evaluated using metrics such as accuracy, precision, recall (sensitivity), specificity, F1-score, and the area under the receiver operating characteristic curve (AUC). For imbalanced datasets, F1-score and AUC are considered more informative than accuracy alone. Confusion matrix analysis is also employed to assess class-wise performance and identify common misclassification patterns.

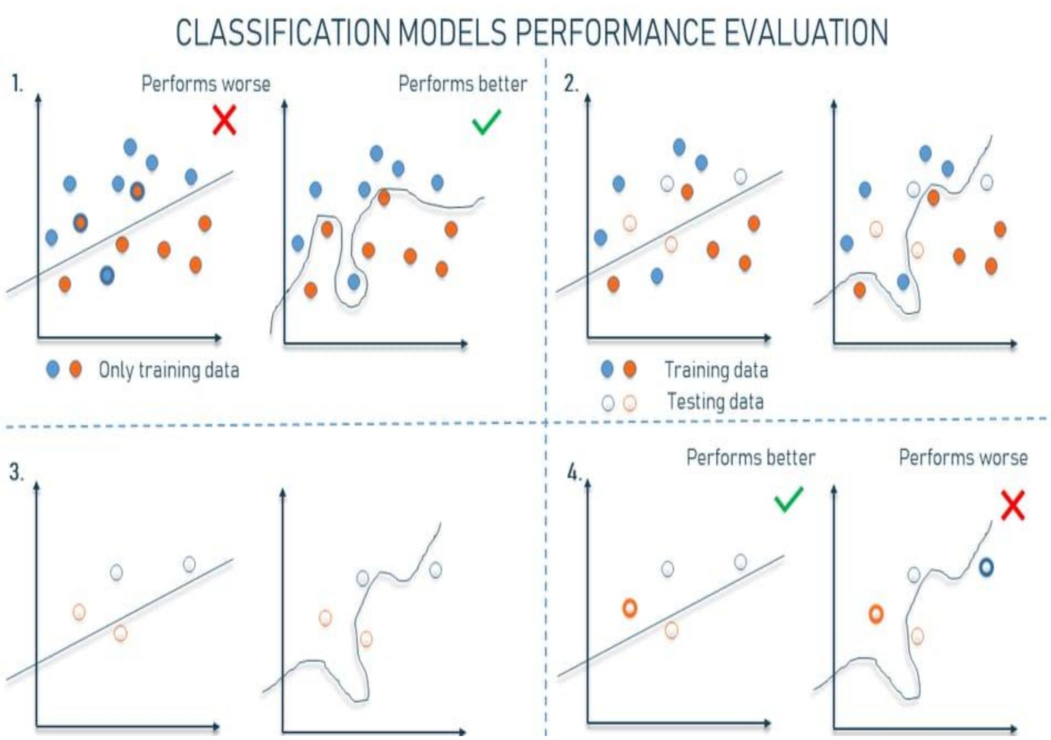


**Figure 11**. Performance Evaluation Metrics for Deep-Learning-Based Skin Cancer Classification

### *3.5. Challenges and Limitations*

Despite promising results, several challenges limit the clinical deployment of deep-learning-based skin cancer classifiers. These include overfitting on small datasets, dataset bias toward lighter skin tones, high computational cost of deep architectures, and limited generalization across datasets acquired from different imaging devices and populations. Additionally, many high-performing models lack interpretability, which may reduce clinician trust and hinder adoption in real-world settings.

## 4. Types of Skin Cancer and Commonly Used Datasets

This section presents an overview of the most common types of skin cancer relevant to automated diagnosis, followed by a summary of widely used public datasets employed for training and evaluating deep-learning-based skin cancer detection systems.

### *4.1. Types of Skin Cancer*

Skin cancer encompasses a range of malignant and pre-malignant conditions that differ in appearance, severity, and metastatic potential. Understanding these lesion types is essential for developing reliable classification models.

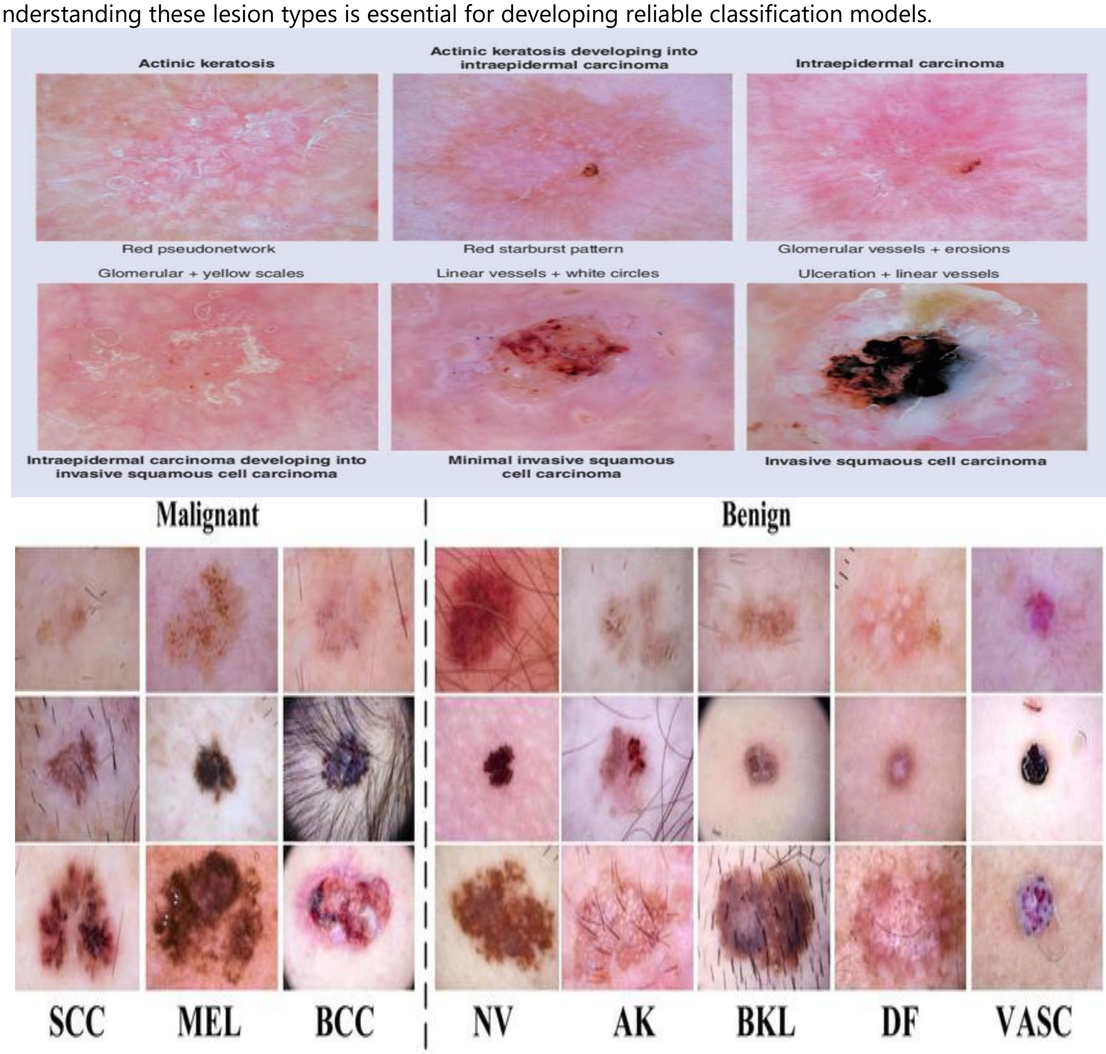


**Figure 12.** Common types of skin cancer and pre-malignant skin lesions frequently encountered in dermoscopic image analysis.

#### *4.1.1. Melanoma*

Melanoma is considered the most aggressive and life-threatening form of skin cancer due to its high potential for metastasis. It can develop on normal skin or arise from pre-existing moles and may appear on both sun-exposed and non-exposed areas of the body. Early detection is critical, as timely treatment significantly improves survival outcomes.

#### *4.1.2. Dysplastic Nevi*

Dysplastic nevi, also known as atypical moles, resemble benign moles but exhibit irregular borders, variable coloration, and larger size. Although non-cancerous, they share visual similarities with melanoma and are considered important risk indicators.

#### *4.1.3. Basal Cell Carcinoma (BCC)*
BCC is the most prevalent form of skin cancer and commonly occurs in sun-exposed areas such as the face, neck, and arms. It often appears as a pearly bump or pinkish lesion and typically grows slowly. While BCC rarely metastasizes, delayed treatment can lead to extensive tissue damage.

#### *4.1.4. Squamous Cell Carcinoma (SCC)*
SCC is another common skin cancer that usually develops on chronically sun-exposed skin. It may present as a scaly patch, firm nodule, or non-healing sore. SCC has a higher risk of invasion and metastasis than BCC if left untreated.

#### *4.1.5. Actinic Keratoses (AKs)*
Actinic keratoses are pre-malignant lesions caused by prolonged UV exposure. They appear as rough, scaly patches and have the potential to progress into SCC. Early identification and treatment of AKs are important to prevent malignant transformation.

### *4.2. Publicly Available Skin Cancer Datasets*
Public datasets play a vital role in advancing deep-learning-based skin cancer research by enabling benchmarking, reproducibility, and comparative evaluation.

#### *4.2.1. HAM10000*
HAM10000 contains 10,015 dermoscopic images spanning seven diagnostic categories, including melanoma, basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, vascular lesions, and melanocytic nevi.

#### *4.2.2. PH2*
The PH2 dataset consists of 200 dermoscopic images with expert-provided annotations, including lesion segmentation and clinical diagnosis. It is commonly used for segmentation and small-scale classification studies.

#### *4.2.3. ISIC Archive*
The ISIC archive is the largest and most widely used repository of dermoscopic images, encompassing multiple benchmark datasets released between 2016 and 2020.

- **ISIC 2016:** Binary classification of melanoma and benign nevi
- **ISIC 2017:** Three-class dataset including melanoma, seborrheic keratosis, and benign nevi
- **ISIC 2018:** Large-scale multi-class dataset with over 12,500 training images
- **ISIC 2019:** Eight-class dataset with metadata such as patient age and lesion location
- **ISIC 2020:** Binary classification dataset with over 33,000 images

## 5. Computational Resources and Implementation Considerations
The successful development and deployment of deep-learning-based skin cancer classification systems depend heavily on the availability of adequate computational resources and practical implementation strategies. The computational requirements vary significantly based on model architecture, dataset size, training strategy, and intended deployment environment. Most deep learning models for skin cancer diagnosis are trained using graphics processing units (GPUs) due to their ability to perform parallel computations efficiently. Studies have reported the use of both consumer-grade GPUs (e.g., NVIDIA GTX and RTX series) and high-performance GPUs (e.g., NVIDIA Tesla and Quadro series) to accelerate training and inference. Memory requirements typically range from 8 GB to 64 GB of system RAM, depending on batch size, image resolution, and network depth. High-capacity storage is also necessary to manage large dermoscopic image datasets and trained model checkpoints. From an implementation perspective, training deep CNN models with high computational complexity can pose challenges for real-time clinical deployment, particularly in resource-constrained environments such as outpatient clinics or mobile healthcare settings. As a result, there has been increasing interest in lightweight architectures and model optimization techniques, including parameter pruning, quantization, and knowledge distillation, to reduce inference latency and hardware dependency. In the context of the United States healthcare system, implementation considerations also extend beyond hardware availability. Integration with existing clinical workflows, interoperability with electronic health record (EHR) systems, data privacy compliance, and scalability across healthcare facilities are critical factors. Efficient deployment strategies, such as cloud-based inference platforms and edge-computing solutions, are being explored to balance computational efficiency with clinical usability.
Overall, optimizing computational resource utilization while maintaining diagnostic accuracy is essential for enabling the practical translation of deep-learning-based skin cancer diagnostic systems from research laboratories to real-world clinical environments.

**6. Challenges, Limitations, and Open Research Issues**

Despite the significant progress of deep-learning-based approaches for skin cancer detection and classification, several challenges continue to limit their effective deployment in real-world clinical environments, particularly within the United States healthcare system. A major limitation is the restricted availability of large, well-annotated, and clinically diverse datasets, which often suffer from severe class imbalance and bias toward benign lesions, reducing model sensitivity for high-risk cancers such as melanoma. Additionally, the underrepresentation of diverse skin tones in existing datasets introduces skin-tone bias, raising serious concerns regarding diagnostic equity across the heterogeneous U.S. population. Deep learning models also frequently exhibit overfitting and limited generalization when evaluated across datasets collected from different institutions, imaging devices, and patient populations. High computational complexity further constrains real-time deployment, especially in resource-limited clinical settings, while the black-box nature of many deep neural networks limits interpretability and clinician trust. Moreover, practical challenges related to integration with clinical workflows, interoperability with electronic health record systems, data privacy compliance, and regulatory approval remain significant barriers. Addressing these interconnected challenges is essential for advancing deep-learning-based skin cancer diagnostic systems from experimental research tools to reliable and clinically deployable decision-support solutions in the United States.

**7. Future Research Directions**

Future research in deep-learning-based skin cancer diagnosis should focus on addressing existing limitations while enhancing clinical applicability within the United States healthcare system. One critical direction involves the development of large-scale, diverse, and demographically representative datasets that include variations in skin tone, age, and lesion characteristics to ensure equitable diagnostic performance across populations. Emphasis should also be placed on improving model generalization through multi-center studies and cross-dataset validation using data collected from different clinical institutions and imaging devices. The integration of explainable artificial intelligence (XAI) techniques represents another important research avenue, as interpretable models can improve clinician trust, support regulatory approval, and facilitate adoption in routine clinical workflows. Additionally, future efforts should prioritize the design of lightweight and computationally efficient models suitable for deployment on mobile devices, edge platforms, and resource-constrained clinical settings. Privacy-preserving learning strategies, such as federated learning, should be explored to enable collaborative model training across healthcare institutions while maintaining patient data confidentiality. Finally, rigorous real-world clinical validation, including prospective studies and integration with electronic health record systems, is essential for translating deep-learning-based skin cancer diagnostic systems into reliable and scalable clinical decision-support tools across the United States.

**8. Conclusion**

Deep learning has demonstrated substantial potential for improving the accuracy and efficiency of automated skin cancer detection and classification using dermoscopic images within the United States healthcare landscape. This article provided a comprehensive analysis of deep-learning-based approaches, encompassing classification frameworks, convolutional neural network architectures, transfer learning strategies, classification paradigms, commonly used datasets, and computational resource requirements relevant to U.S.-based research and clinical settings. The findings indicate that CNN-based models can effectively learn hierarchical and discriminative features, often achieving diagnostic performance comparable to experienced dermatologists under controlled experimental conditions. Despite these advancements, several challenges continue to limit real-world clinical deployment in the United States. These include the limited availability of large, diverse, and representative annotated datasets, class imbalance, insufficient representation of diverse skin tones, high computational complexity of deep architectures, and limited generalization across datasets and patient populations. Additionally, concerns related to model interpretability, clinical reliability, regulatory compliance, and real-time deployment within U.S. healthcare systems remain significant barriers to adoption. Future research should prioritize the development of lightweight and explainable deep learning models, the inclusion of diverse and representative U.S. patient cohorts, and rigorous validation in real clinical environments. Addressing these challenges is critical for translating deep-learning-based skin cancer diagnostic systems into reliable and trustworthy clinical decision-support tools across the United States.

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