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Skin cancer detection advancements by employing machine learning and deep learning: A comprehensive review

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A B S T R A C T

A thorough analysis of developments in machine learning (ML) and deep learning (DL) technologies for skin cancer diagnosis is provided in this research. It investigates how ML and DL could improve the precision and effectiveness of melanoma, basal cell carcinoma, and squamous cell carcinoma detection. By looking at current studies, the study emphasizes the use of neural networks, convolutional neural networks (CNNs), support vector machines (SVM), random forests, and k-nearest neighbors (KNN) in the diagnosis of skin cancer. Key findings show that DL models, including VGG, ResNet, and Inception benefit from huge datasets and sophisticated data augmentation strategies to attain high accuracy, sensitivity, and specificity. The paper also discusses the challenges and limitations associated with these technologies, such as the requirement for extensive annotated datasets. The study concludes with a call for collaboration to overcome current challenges and enhance the practical application of ML and DL in skin cancer detection.

1. Introduction

Skin cancer ranks among the most popular malignancies worldwide, with millions of new diagnoses annually. The primary types—melanoma, basal cell carcinoma, and squamous cell carcinoma—vary in severity, frequency, and treatment complexity. Melanoma, although less frequent, is the deadliest due to its high metastatic potential. Conversely, squamous cell carcinoma and basal cell carcinoma are more prevalent but typically less aggressive. Early and precise detection is crucial for enhancing patient outcomes, as the likelihood of favorable outcomes significantly increases when skin cancer is identified in its initial stages[1].

Although early diagnosis is essential, traditional diagnostic techniques for skin cancer, such as dermatological visual inspections followed by histopathological analysis of biopsied tissues, are not without limitations. These methods are often subjective, reliant and time-intensive, on the clinician's expertise, which can result in variability in diagnostic accuracy. Consequently, there is an urgent demand for innovative diagnostic tools that enhance clinicians' capabilities and offer more reliable and efficient diagnostic outcomes[2].

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Fig. 1. Examples of skin cancer[3]

Recent developments in deep learning (DL) and machine learning (ML) have shown great promise for enhancing diagnosis processes for various medical conditions, including skin cancer. ML and DL methods utilize large datasets to create models that can detect patterns and produce highly accurate predictions. In particular, deep learning techniques, especially convolutional neural networks (CNNs), have revolutionized the field of image analysis. These techniques have been effectively used in medical imaging, producing excellent outcomes in terms of skin lesion detection and categorization[4].

This paper aims to deliver an in-depth analysis of the latest advancements in machine learning (ML) and deep learning (DL) for skin cancer detection. The main objectives are to assess the current landscape of ML and DL technologies, their specific applications in diagnosing different types of skin cancer, and the challenges and limitations associated with these methods. The ultimate goal is to highlight the transformative potential of these technologies in improving diagnostic accuracy, reducing the strain on healthcare systems, and ultimately saving lives through earlier detection[5].

To achieve these objectives, the paper begins with an overview of skin cancer, its classifications, and traditional diagnostic methods. This is followed by an in-depth exploration of ML algorithms commonly employed in skin cancer detection, including support vector machines (SVMs), random forests, neural networks, and k-nearest neighbors (KNN). The subsequent section focuses on DL techniques, particularly CNN architectures, associated datasets, training strategies, and performance evaluation metrics. Ethical and legal considerations are also examined, emphasizing the significance of patient privacy, regulatory compliance, and mitigating biases in ML and DL models. the paper emphasizes key findings, examines future implications for skin cancer detection, and stresses the importance of ongoing research and development in this area.

1.1 Background

Unchecked skin cell development leads to skin cancer, a prevalent cancer in the world. Melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC) are its three main manifestations. Since each type varies in frequency, severity, and complexity of therapy, early discovery is crucial to improving treatment results[6]. Melanoma, although representing a smaller fraction of skin cancer cases, is the most lethal form due to its significant metastatic potential and high mortality rate[7]. Excessive and sporadic exposure to ultraviolet (UV) radiation is frequently linked to melanoma, a kind of skin cancer that arises in melanocytes, the cells that produce color in the skin. Both artificial sources, such as tanning beds, and natural sunshine can contribute to this. Its incidence is notably increasing, particularly among fair-skinned individuals in regions with elevated UV radiation. Early detection is paramount, as melanoma can rapidly metastasize. When diagnosed in its early stages, surgical excision often results in curative outcomes, achieving a five-year survival rate exceeding 95%. Conversely, advanced melanoma necessitates complex treatments, such as immunotherapy, targeted therapy, or chemotherapy, leading to significantly reduced survival rates[8].

The most prevalent type of skin cancer is basal cell carcinoma (BCC), which makes up about 80% of cases. It starts in the basal cells, which are found in the epidermis' lowest layer. Long-term exposure to UV radiation is the main cause of BCC, which usually affects parts of the face, neck, ears, shoulders, and back that are exposed to the sun[8,9]. BCC seldom spreads to other parts of the body and grows slowly, but if left untreated, it can cause severe local tissue damage and deformity. It often presents as pearly or waxy nodules with visible blood vessels or as flat, scar-like patches. Standard treatment usually involves surgical removal, with additional options like cryotherapy, topical agents, and radiation therapy for more extensive or hard-to-reach cases[10.11].

The squamous cells that make up the bulk of the skin's outer layers are the source of squamous cell carcinoma (SCC), the second most prevalent kind of skin cancer. Compared to basal cell carcinoma (BCC), SCC is more aggressive and has a larger chance of spreading if treatment is delayed[12]. It usually appears on places like the head, neck, and arms that are frequently exposed to the sun and is mostly brought on by cumulative exposure to

UV radiation. Scaly red patches, open sores, or elevated growths with core depressions that may crust or bleed are clinical manifestations of SCC. Early-stage SCC can usually be treated effectively with surgical excision, whereas advanced cases often require adjunctive therapies such as radiation or systemic treatments[13].

The global incidence of skin cancer has been steadily increasing, driven by factors such as heightened UV exposure due to sunbathing and tanning practices, aging populations, and improvements in detection and reporting systems[14]. In areas with predominantly fair-skinned populations, skin cancer represents a major public health issue, leading to considerable healthcare expenses and morbidity. For instance, with over 5 million instances reported annually, skin cancer is the most common cancer diagnosed in the US[15]. Successful treatment outcomes for skin cancer depend on early detection. Patients diagnosed at an early stage have significantly better prognoses compared to those with advanced disease. For example, melanoma detected early has a five-year survival rate exceeding 95%, but this rate drops markedly once the cancer spreads to distant sites[16-18]. Early diagnosis enables less invasive treatments, reduces healthcare costs, and improves patient quality of life. Despite the availability of effective treatments for early-stage skin cancer, traditional diagnostic methods face challenges, such as dependence on expert clinical evaluation and histopathological confirmation[15]. Visual examination by dermatologists, followed by biopsy and microscopic analysis, remains the diagnostic gold standard. However, this approach is constrained by subjectivity, diagnostic variability, and the need for specialized expertise[19-21].

The integration of advanced diagnostic tools, especially ML and DL, presents promising solutions to these limitations[22]. ML and DL techniques leverage extensive datasets to create models that can identify patterns and generate highly accurate predictions. Among these techniques, deep learning, particularly convolutional neural networks (CNNs), has revolutionized image analysis and demonstrated exceptional effectiveness in detecting and classifying skin lesions[23]. Using techniques including supervised learning, unsupervised learning, and reinforcement learning, machine learning uses algorithms to analyze data and produce predictions[24-25]. In skin cancer detection, these ML algorithms scrutinize medical images to recognize features indicative of malignancy. Deep learning, a distinct subset of ML, uses multi-layered neural networks to detect complex patterns within data[26]. CNNs, a prominent deep learning architecture, are particularly effective for image analysis tasks and have achieved significant success in medical imaging applications. Through early detection, the use of ML and DL in skin cancer detection has the potential to significantly improve diagnosis accuracy, lower healthcare costs, and save lives[27]. These technologies assist clinicians by providing supplementary insights, identifying subtle patterns undetectable to the human eye, and standardizing diagnostic procedures to minimize variability. Nevertheless, successful implementation in clinical practice requires addressing critical challenges, such as the requirement for extensive annotated datasets, the risk of overfitting, and the opaque decision-making processes inherent to these models[28].

1.2 Motivation

Despite the effectiveness of current diagnostic methods for skin cancer, they are accompanied by considerable limitations. Conventional detection predominantly relies on visual examination by dermatologists, followed by histopathological analysis of biopsied tissue samples. While this approach remains the gold standard, it is inherently subjective, often resulting in diagnostic variability due to differences in the expertise and perceptual biases of clinicians. Such subjectivity can lead to misdiagnoses, manifesting as either unnecessary biopsies or delays in initiating treatment. Furthermore, histopathological analysis is a time-intensive, resource-demanding, and invasive procedure, often accompanied by significant delays in results, thereby contributing to patient anxiety and potentially postponing critical treatment interventions. Considering these challenges, there is a strong need for innovative diagnostic tools to supplement and improve current workflows. ML and DL technologies present valuable alternatives by utilizing extensive datasets and advanced algorithms to improve diagnostic accuracy, efficiency, and reliability. ML algorithms are capable of processing vast amounts of medical imaging data, identifying intricate patterns that may indicate malignancy. Likewise, DL models, particularly convolutional neural networks (CNNs), excel at analyzing medical images and accurately differentiating between benign and malignant lesions. The integration of ML and DL into the diagnostic pipeline offers numerous advantages, including the ability to provide rapid, real-time analysis, minimize diagnostic variability, and deliver objective, data-driven evaluations. By facilitating early detection and enabling the formulation of personalized treatment strategies, these technologies have the potential to address the shortcomings of traditional methods and revolutionize the field of skin cancer diagnostics. Such advancements are poised to significantly enhance patient outcomes on a global scale.

1.3 Objective

This paper's primary objectives are to provide a thorough analysis of recent advancements in machine learning (ML) and deep learning (DL) technologies for skin cancer detection, pinpoint the present obstacles to advancement in this area, suggest possible research avenues to address these obstacles, and improve the effectiveness of these technologies[29]. To fulfill these objectives, the paper is organized to address the following specific goals:

1.3.1 Reviewing Recent Advancements in ML and DL Technologies for Skin Cancer Detection:

This paper systematically examines the latest developments in the application of ML and DL technologies to skin cancer diagnostics. Recent innovations in these fields have demonstrated considerable potential in improving diagnostic accuracy and efficiency[30]. The review focuses on various ML algorithms and DL architectures that have been successfully applied in recent studies. The key technologies covered include:

Neural Networks and Convolutional Neural Networks (CNNs): A detailed analysis of CNNs, renowned for their efficacy in image analysis tasks. The discussion includes an exploration of prominent CNN architectures such as VGG, ResNet, and Inception, which have exhibited superior performance in classifying skin lesions[31-33].

Support Vector Machines (SVM): This paper explores the application of support vector machines (SVMs) in classifying skin cancer images, highlighting their capacity to handle high-dimensional data and their effectiveness in differentiating between various types of skin lesions[34].

Random Forests: A summary of how Random Forest algorithms is applied in skin cancer detection, emphasizing their capability to manage large datasets and provide robust classification through ensemble learning techniques[7].

K-Nearest Neighbors (KNN): A review of KNN applications in skin cancer classification, emphasizing its simplicity and effectiveness in specific diagnostic contexts[21].
Other Emerging Technologies: This paper discusses innovative ML and DL approaches, such as generative adversarial networks (GANs) for data augmentation and semi-supervised learning techniques that utilize unlabeled data. Both methods have shown promising potential in recent research[35].

1.3.2 Identifying Current Challenges in ML and DL Applications:

Although significant progress has been made, several challenges remain that must be overcome to enable the widespread adoption and integration of ML and DL technologies in clinical settings for skin cancer detection[36]. This paper aims to identify and critically examine these challenges:

Data Requirements: The need for large, annotated datasets to train robust models, including challenges associated with obtaining high-quality, diverse datasets that accurately represent varying skin types, demographics, and lesion characteristics[37].

Overfitting: Deep learning models have a tendency to overfit, resulting in excellent performance on training data but a reduced ability to generalize to new, unseen data. This section explores strategies to mitigate overfitting, including data augmentation, dropout methods, and regularization techniques[38].

Model Interpretability: The opaque decision-making processes of deep learning models, often described as the "black box" problem, which can hinder clinical acceptance and trust. The paper examines approaches to improve interpretability and transparency, such as saliency maps and attention mechanisms[39].

Performance Variability: The inconsistency of model performance across different populations and clinical environments, with a focus on addressing biases in ML/DL models to ensure equitable healthcare outcomes across diverse patient groups[40].

Ethical and Legal Considerations: Ethical and legal considerations, including patient privacy, data security, and adherence to regulatory standards, are crucial. The paper underscores the significance of maintaining ethical and legal compliance to ensure the responsible integration of ML and DL technologies in clinical settings[41].

2. Skin Cancer: An Overview

The unchecked growth of aberrant skin cells is an indicator of skin cancer, a common kind of cancer worldwide. Melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC) are the three main forms in which it typically presents. Each type exhibits unique clinical features, risk factors, and therapeutic implications, necessitating a comprehensive understanding for accurate diagnosis and effective management[42].

2.1 Types of Skin Cancer

Skin cancer, as depicted in **Fig. 2**, represents a major global health concern and typically appears in three primary forms: melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). Each type exhibits unique characteristics, risk factors, and treatment approaches, highlighting the necessity of a thorough understanding for accurate diagnosis and effective management[43]. Melanoma is the most lethal form of skin cancer due to its high metastatic potential and elevated mortality rate. It originates in melanocytes, the cells responsible for producing pigment, and commonly develops on men's trunk and on women's legs[44]. Risk factors include excessive ultraviolet (UV) exposure, fair skin, family history of melanoma, and atypical moles. Clinically, melanoma is often identified through the ABCDE criteria: asymmetry, irregular borders, color variations, diameter greater than 6mm, and evolving characteristics[45]. Additional symptoms may include itching, tenderness, or bleeding. Subtypes such as superficial spreading melanoma, nodular melanoma, lentigo maligna melanoma, and acral lentiginous melanoma exhibit unique clinical and histological features[43]. Early-stage melanoma is typically treated with surgical excision, while advanced stages may require immunotherapy, targeted therapy, chemotherapy, or radiation therapy. Innovations like immune checkpoint inhibitors and BRAF inhibitors have significantly improved survival rates for advanced cases[46]. About 80% of all occurrences of skin cancer are basal cell carcinoma (BCC), making it the most prevalent kind. It starts in the epidermis' basal cells and is mostly brought on by extended exposure to UV light[47]. BCC typically appears on sun-exposed areas and can present in various forms, including nodular BCC, superficial BCC, morpheaform BCC, and pigmented BCC[48]. Although BCC grows slowly and rarely metastasizes, untreated cases can lead to significant local tissue damage.

Fig. 2. Types of Skin Cancer[18]

Table 1. Classification of Skin Cancer Types

Type	Description	Common Locations	Treatment Options
Melanoma	Most dangerous, with high metastatic potential. Arises from melanocytes.	Trunk, legs, other sun-exposed areas.	Surgical excision, immunotherapy, targeted therapy, chemotherapy, radiation therapy.
Basal Cell Carcinoma (BCC)	Most prevalent, slow-growing, rarely metastasizes. Originates in basal cells.	Face, ears, neck, scalp, shoulders, back.	Surgical excision, Mohs surgery, cryotherapy, topical treatments, radiation therapy.
Squamous Cell Carcinoma (SCC)	More aggressive, higher metastasis risk. Develops from squamous cells.	Head, neck, hands, arms, sun-exposed areas.	Surgical excision, Mohs surgery, radiation therapy, photodynamic therapy, systemic treatments.

The size, location, and depth of the tumor will determine the best course of treatment for BCC, which includes surgical excision, Mohs micrographic surgery, cryotherapy, topical treatments, and radiation[49]. The second most common kind of skin cancer, squamous cell carcinoma (SCC), develops from the squamous cells in the epidermis[24]. SCC is more aggressive than BCC, with a greater risk of metastasis. It commonly develops on sun-exposed areas and often presents as actinic keratosis or Bowen's disease in its early stages. Invasive SCC appears as red, scaly patches, open sores, or wart-like growths that may bleed or crust[50,51]. Treatment typically involves surgical excision, with additional options such as Mohs surgery, radiation therapy, or systemic treatments for advanced cases. Risk factors for squamous cell carcinoma include prolonged UV exposure, fair skin, a history of sunburn, and exposure to carcinogens like tobacco or HPV[21]. The distinct features and treatment requirements of melanoma, BCC, and SCC highlight the necessity for tailored diagnostic and therapeutic approaches. Accurate identification and differentiation are crucial, given the significant variation in treatment protocols and prognostic outcomes among these types.

2.2 Traditional Diagnostic Methods

Conventional diagnostic methods for skin cancer usually include clinical examination and histopathological analysis, which, while effective, are associated with notable limitations and challenges[52]. Dermatologists rely on visual inspection using the ABCDE criteria, often supplemented by dermoscopy to improve diagnostic accuracy[53]. Despite its benefits, dermoscopy relies significantly on the clinician's expertise, leading to variability in diagnosis[54]. Biopsy, considered the gold standard for a definitive diagnosis, involves collecting a tissue sample for histopathological analysis. Although accurate, this procedure is invasive and time-consuming, with potential discomfort for patients and delays in treatment planning. Furthermore, histopathological interpretation is subject to variability among pathologists, particularly in complex cases[55].

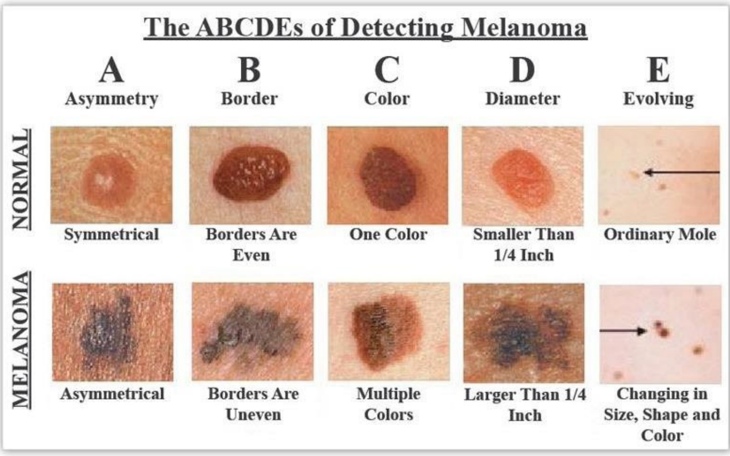

Fig. 3. ABCDE criteria[56]

The challenges of traditional diagnostic methods underscore the need for innovative solutions, such as ML and DL, to enhance diagnostic accuracy and efficiency. These technologies promise to address the limitations of conventional approaches, offering significant potential for improving patient outcomes.

3. Machine Learning in Skin Cancer Detection

Machine learning (ML) has become a transformative tool in medical diagnostics, greatly improving the accuracy and efficiency of skin cancer detection, as shown in **Fig. 4.** By leveraging large datasets and advanced algorithms, ML can detect patterns and features in medical images that often surpass human perceptual abilities. This section explores the foundational principles of ML, its application in skin cancer detection, and the specific algorithms that show significant potential in this field[129].

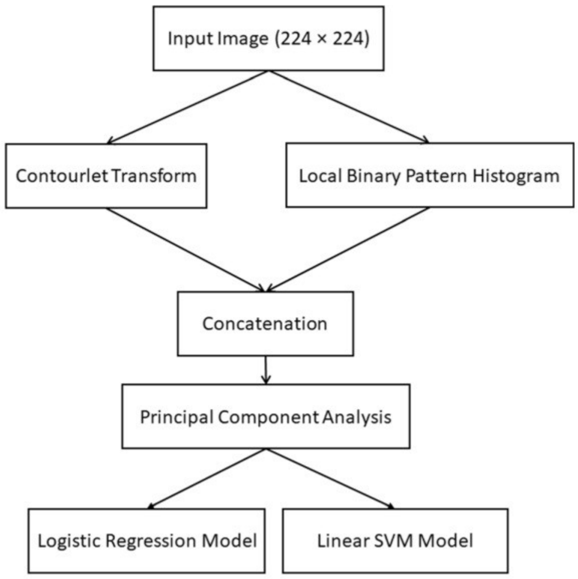

Fig. 4. Machine learning in skin cancer detection[57]

3.1 Basic Concepts

A collection of methods and algorithms known as machine learning (ML) allow computers to learn from data and provide predictions or judgments. Within medical imaging, ML has become instrumental in analyzing complex images, identifying patterns, and supporting diagnostic processes. This section offers an overview of widely used ML methodologies in medical imaging, including ensemble learning techniques, supervised learning, and unsupervised learning[58].

Supervised Learning: Training models with labeled datasets—where each input is associated with its matching output—is known as supervised learning. The goal is to develop a mapping function that can forecast results for new, unobserved data. In medical imaging, supervised learning is commonly used for classification tasks, such as distinguishing between benign and malignant skin lesions, and regression tasks, like estimating tumor size[49]. Among supervised learning techniques, Support Vector Machines (SVMs) are particularly efficient for binary classification. SVMs operate by finding the best hyperplane in the feature space that optimizes the margin between the two classes. SVMs are ideal for high-dimensional data because they can handle non-linear interactions by integrating kernel functions[59].

Neural Networks: A key element of supervised learning, especially in image analysis, are neural networks. These networks are made up of layers of linked neurons that are arranged to process information in a hierarchical fashion. A specific neural network design called Convolutional Neural Networks (CNNs) excels at tasks involving images. CNNs use fully connected layers to do the final classification, pooling layers to reduce the dimensionality of the input, and convolutional layers to extract features like edges and textures. CNNs have transformed medical imaging by greatly increasing diagnostic task accuracy[60].

Unsupervised Learning: Unsupervised learning trains models on data without labeled outcomes, aiming to uncover hidden patterns or intrinsic structures. In medical imaging, unsupervised learning is applied to clustering and dimensionality reduction, helping to uncover patterns in large datasets and streamline data analysis[61]. Common algorithms include K-means clustering, which organizes data into clusters based on similarity, and Principal Component Analysis (PCA), which reduces dimensionality by transforming data into orthogonal components that capture the highest variance[62].

Ensemble Learning: Ensemble learning integrates multiple models to form a composite model that achieves enhanced performance. Random Forests, an ensemble method, consist of numerous decision trees trained on data subsets. Predictions are aggregated through majority voting (classification) or averaging (regression), resulting in robust and accurate models[63]. Boosting algorithms, such as AdaBoost and Gradient Boosting, sequentially train models, where each new model focuses on correcting the errors of its predecessors, yielding highly predictive models[64].

K-Nearest Neighbors (KNN): KNN is a simple yet effective algorithm that classifies data points by evaluating their proximity to labeled neighbors within the feature space. It is particularly effective for small-scale medical imaging tasks[65].

3.2 Applications and Related Work

Recent studies have highlighted the efficacy of ML techniques in skin cancer diagnostics: Al-Rakhami et al.[36] employed deep convolutional neural networks (DCNNs) with federated learning to enhance diagnostic accuracy while preserving data privacy. Their system demonstrated robust performance in skin cancer classification. Afroz et al.[128] utilized CNNs, achieving 93% training accuracy and 100% testing accuracy for melanoma classification, underscoring the diagnostic precision of CNNs. Mridha et al. (2023) addressed class imbalance in CNN-based classification and incorporated Explainable AI techniques like Grad-CAM, achieving 82% accuracy on the HAM10000 dataset[66]. Tjahjamoorniarsih et al. (2024) applied AlexNet to dermatoscopic images, achieving 80% accuracy, emphasizing the feasibility of CNNs for clinical use[67].

Table 2. Skin Cancer Diagnosis, Detection and Classification

Modality	Method	Remarks	Performance Metrics	Ref.
Skin Cancer Diagnosis	Yolo Deep Neural Network	Classification of nine skin cancer types using YOLOv3 andYOLOv4 with data augmentation.	mAP: YOLOv3 88.03%, YOLOv4 86.52%.	68
Skin Cancer Detection	CNN	Comparative analysis of AlexNet, ResNet50, and customized CNN for melanoma detection.	Achieved high classification accuracy.	69
Skin Cancer Classification	CNN	Classified skin cancer into benign and malignant categories with a training accuracy of 92%.	Testing accuracy exceeded 95%.	70

The results highlight how ML has the potential to revolutionize skin cancer screening. To promote broad acceptance and optimize efficacy, future studies should concentrate on resolving issues including data constraints, model interpretability, and smooth integration into clinical processes.

3.3 Neural Networks and Convolutional Neural Networks (CNNs)

Neural networks are made up of linked nodes (neurons) that process and transmit information; they are modeled after the structure and operation of the human brain. These networks are especially effective for applications like image analysis because they use training to identify intricate patterns in data. Because CNNs, a specific kind of neural network, can automatically and adaptively learn spatial feature hierarchies from input pictures, they are very useful for image analysis applications like skin cancer diagnosis[71].

An input layer, one or more hidden layers, and an output layer make up a neural network. Neurons in each layer are coupled to those in the one below. In order to produce outputs, neurons apply activation functions to the weighted sum of their inputs, each connection having a corresponding weight. The training process involves modifying these weights through backpropagation to reduce the error between predicted outputs and actual labels. Although traditional neural networks can model complex data relationships, they often face challenges with high-dimensional data, such as images, due to their computational demands and large number of parameters[72,73].

CNNs are very successful for image analysis tasks because they address these difficulties using a particular design that consists of convolutional layers, pooling layers, and fully connected layers[74]. Convolutional layers create feature maps that emphasize important patterns like edges, textures, and forms by applying filters (kernels) to the input picture. While the upper layers record more complex characteristics, the lower levels concentrate on identifying basic patterns. Pooling layers, commonly using max pooling, reduce the size of the feature maps, improving computational efficiency and stability while retaining essential information. Lastly, fully connected layers integrate the extracted features to make the final classification or regression decision[75,76].

Notable CNN architectures, such as VGG, ResNet, and Inception, have been widely applied to skin cancer detection. VGG networks are characterized by their simplicity and depth, using small convolutional filters and multiple layers. ResNet introduces residual learning with shortcut connections, enabling deeper architectures without vanishing gradient issues. Inception networks employ convolutional filters of different sizes within a single layer, allowing them to capture features at multiple scales. In image classification tasks, variants such as VGG-16, ResNet-50, and Inception-v3 have demonstrated remarkable performance[53, 77].

CNNs have become widely utilized in dermoscopic image analysis for skin cancer detection, as shown in **Fig. 5.** Dermoscopic images contain intricate lesion structures, and CNNs are capable of automatically extracting the relevant features for analysis, such as textures, color patterns, and shapes, aiding in distinguishing between skin cancer types. Training CNNs involves large datasets of annotated dermoscopic images, enabling the network to learn patterns indicative of benign or malignant lesions. These trained models serve as powerful tools to assist dermatologists in early and accurate skin cancer diagnosis[78,79].

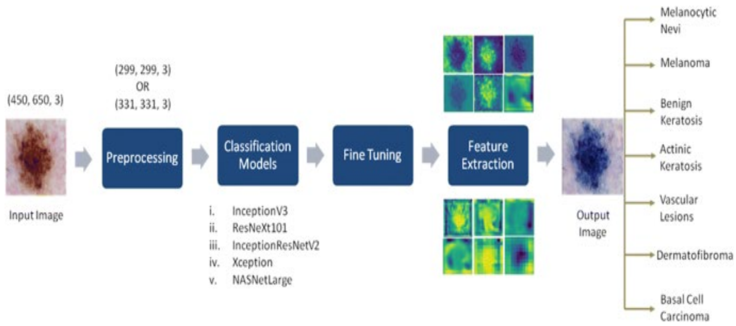

Fig. 5: Classification of skin cancer using deep convolutional neural networks[10,11]

The special benefits of CNNs in tackling the difficulties of skin cancer diagnosis are highlighted in this section. CNNs provide intriguing ways to increase the precision and effectiveness of dermatological diagnostics by leveraging sophisticated designs and huge datasets.

3.4 Support Vector Machines (SVM)

Strong supervised learning techniques called Support Vector Machines (SVMs) are frequently employed in regression, classification, and outlier identification.

Table 3. Comparison of Neural Network Types

Feature	Neural Networks	Convolutional Neural Networks (CNNs)
Architecture	Composed of interconnected nodes (neurons) with layers: input, hidden, and output. Each neuron processes inputs using an activation function.	Specialized for grid data like images. Includes convolutional layers, pooling layers, and fully connected layers.
Core Components	Layers of neurons, each connected to subsequent layer neurons, weights associated with connections.	Convolutional layers apply filters to input, creating feature maps. Pooling layers reduce dimensionality, and fully connected layers make predictions.
Function	Can model complex relationships in data and perform classification, regression, and clustering.	Particularly effective for image analysis by learning spatial hierarchies of features automatically.
Challenges	Requires significant computational resources and parameters for high-dimensional data like images.	Designed to reduce computational load through structured layering and pooling, still requires large datasets for effective training.
Applications	Broad applications across various domains due to its flexibility in modeling data relationships.	Extensively used in image analysis, such as skin cancer detection, through the analysis of detailed features in images.

SVMs have demonstrated exceptional effectiveness in identifying benign and malignant lesions in medical imaging and in the identification of skin cancer. The capacity of SVMs to efficiently handle high-dimensional data and choose the best separating hyperplane that optimizes the margin between classes, which raises classification accuracy, is one of its main advantages[80]. Input data is mapped into a high-dimensional feature space via SVMs, where a linear hyperplane effectively divides the various classes. Finding the hyperplane that maximizes the margin—the distance between the hyperplane and the closest data points from each class—as well as splits the data is the goal. A key component of the SVM method, these crucial points—also referred to as support vectors—are essential for figuring out the position and orientation of the hyperplane[81].

In skin cancer image classification, SVMs are particularly effective because of their ability to manage the high-dimensional and complex nature of medical imaging data. Features like texture, color, and shape descriptors extracted from lesion images are used as inputs to the SVM, allowing for accurate differentiation between benign and malignant lesions[82].

One of the main characteristics of SVMs is their capacity to capture non-linear correlations in the data by mapping input data into higher-dimensional regions using kernel functions. The linear kernel, polynomial kernel, radial basis function (RBF) kernel, and sigmoid kernel are examples of frequently used kernel functions. Because of its ability to capture non-linear patterns, the RBF kernel is frequently used for medical imaging applications like skin cancer diagnosis[83].

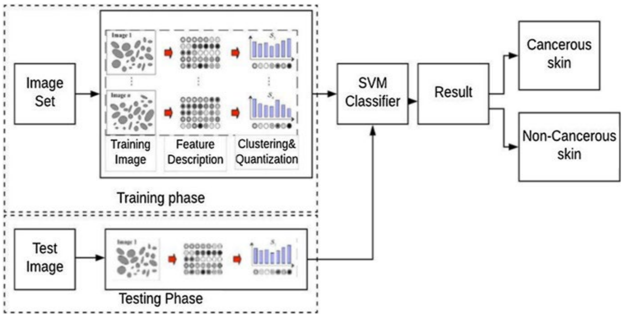

Fig. 6. Support Vector Machine-based early diagnosis of skin cancer[87,88]

Table 4. The summary of modality and methods

Modality	**Method**	**Remarks**	**Performance Metrics and Results**	**Ref.**
Skin Cancer Classification	CNN vs SVM	Comparison of accuracy	CNN: 95.03%, SVM: 93.04%	89
Skin Cancer Classification	ANN vs SVM	Comparison of classifiers	ANN: 98.32%, SVM: 86.17%	90
Skin Cancer Detection	Bendlet Transform with SVM	Feature extraction and classification	High performance using Bendlet	91
Melanoma Diagnosis	SVM with GLCM	Rapid diagnosis system	83% accuracy, 17% error rate	92
Skin Cancer Detection	Mobile-enabled system with SVM	Early detection tool	Sensitivity: 80%, Specificity: 75%	93
Skin Cancer Detection	Bag of Features with SVM	Early diagnosis approach	Accuracy: 85.7%, Sensitivity: 100%	88
Melanoma Detection	SVM-based classification	Image analysis and classification	92.1% accuracy	94
Skin Cancer Detection	SVM vs KNN	Performance comparison	SVM: 94.30%, KNN: 93.99%	95
Skin Cancer Classification	Hybrid CNN and SVM	Model optimization for accuracy	91.5% accuracy with SVM-TPOT	96
Skin Cancer Diagnosis	Bendlet Transform with SVM	Superior to other systems	High accuracy	71
Skin Cancer Detection	SVM vs CNN	Comparison based on accuracy	CNN: 95.91%, SVM: 94.30%	95

An SVM classifier for skin cancer detection goes through a number of phases during training. To improve picture quality and identify pertinent characteristics, preprocessing is first conducted to a labeled collection of skin lesion images. The SVM is trained using feature vectors, which are created by compiling these features. By adjusting the hyperplane to maximize the margin during training, the SVM algorithm gains the ability to differentiate between classes and achieve high classification accuracy[84]. However, challenges in using SVMs for skin cancer detection include selecting appropriate features and tuning hyperparameters. Feature selection is crucial as it directly impacts classifier performance. Commonly used features include color histograms, texture descriptors, and shape features, which capture critical visual attributes of skin lesions. Hyperparameter tuning, involving parameters such as the regularization parameter (C) and kernel-specific parameters, is typically performed using cross-validation to ensure generalizability to unseen data[85]. Another consideration is addressing imbalanced datasets, a common issue in medical imaging where benign cases often outnumber malignant ones. To mitigate this, techniques such as data augmentation, synthetic minority over-sampling technique (SMOTE), and cost-sensitive learning are employed to balance the dataset and improve classifier reliability[86]. SVMs have been effectively used in skin cancer detection, yielding promising results in accuracy, sensitivity, and specificity, as illustrated in Figure 6. Studies have shown that integrating SVMs with advanced feature extraction methods and ensemble learning techniques further enhances their performance, making them a valuable tool in diagnostic workflows[30].

3.5 Random Forest

An ensemble learning method called Random Forest is frequently used for classification and regression problems and has shown great promise in medical imaging applications like the diagnosis of skin cancer. Its strengths lie in handling large datasets, mitigating overfitting, and providing robust and accurate classifications. This section delves into the application of Random Forest in skin cancer detection, highlighting its advantages and implementation process[20].

During the training stage, the Random Forest algorithm builds many decision trees and aggregates their results to provide final recommendations. This approach addresses limitations of single decision trees, such as overfitting and high variance, by introducing randomness in the tree construction process and combining results from multiple trees for more stable and accurate predictions. The ensemble approach of Random Forest improves its ability to generalize to unseen data, making it a dependable tool for medical diagnostics[31].

There are numerous crucial elements involved in using Random Forest to the diagnosis of skin cancer. The first step is gathering a dataset of pictures of skin lesions and labeling them with diagnoses like benign or malignant. To enhance picture quality and extract significant elements including color histograms, texture indicators, and shape attributes, preprocessing techniques are employed. These characteristics provide a thorough depiction of the visual characteristics of the lesions[72].

Through a technique known as bootstrap aggregating, or bagging, the algorithm uses several subsets of data and attributes to generate numerous decision trees. In order to create bootstrap samples, the training data is randomly sampled with replacement. A random subset of characteristics is chosen at each split in order to construct each tree. By ensuring the model does not rely too much on any one characteristic or subset of data, this use of randomization helps avoid overfitting[97].

During training, each decision tree independently learns to classify lesions based on the selected features. The diversity among the trees results in varying predictions for the same input, and the final classification is made by combining the predictions from all the trees—usually through majority voting for classification tasks or averaging for regression tasks. This ensemble approach improves the model's robustness and accuracy by utilizing the collective insights of multiple trees[98].

Random Forest is highly effective at managing high-dimensional data and large feature sets, as it selects the most relevant features during tree construction. This helps reduce dimensionality and emphasizes the most informative aspects of the data. This capability is especially valuable in medical imaging, where irrelevant or redundant features can degrade classifier performance[50].

Another key advantage is its ability to estimate feature importance, analyzing each feature's contribution to the overall classification performance. This information provides insights into the critical attributes for differentiating between benign and malignant lesions, aiding researchers and clinicians in developing more effective diagnostic tools[92].

Imbalanced datasets, common in medical imaging due to the higher prevalence of benign cases, present a challenge in skin cancer detection. Random Forest addresses this issue through techniques like balanced random forests, which adjust sampling processes to ensure adequate representation of minority classes. This adjustment improves classification performance across all classes, enabling accurate detection of malignant lesions even in imbalanced datasets[99]. As shown in **Fig. 7**, Random Forest has proven effective in skin cancer detection, delivering promising outcomes. Multiple studies have demonstrated high accuracy, sensitivity, and specificity in distinguishing between benign and malignant lesions. Its flexibility and strength make it an essential tool for medical image analysis, capable of managing the complexity and variability found in skin lesion data[100].

3.6 Related Work

The incorporation of ML and DL techniques has greatly enhanced skin cancer detection and classification, enabling improvements in diagnostic accuracy and efficiency. Numerous studies have explored diverse methodologies and algorithms to enhance these outcomes.

Kavitha et al.[102] proposed a hybrid approach that combines Partial Differential Equation (PDE) with Fuzzy Clustering (FC) for segmenting skin cancer images. The model obtained a classification accuracy of 97.7% with Support Vector Machine (SVM) classifiers on the ISIC dataset by employing the ABCD scoring approach for feature extraction. Saravanan et al.[101] developed an active hybrid machine learning technique that combines neural networks with additional classifiers to predict and classify melanoma. By employing majority voting, their ensemble approach leveraged the strengths of different classifiers to achieve enhanced precision.

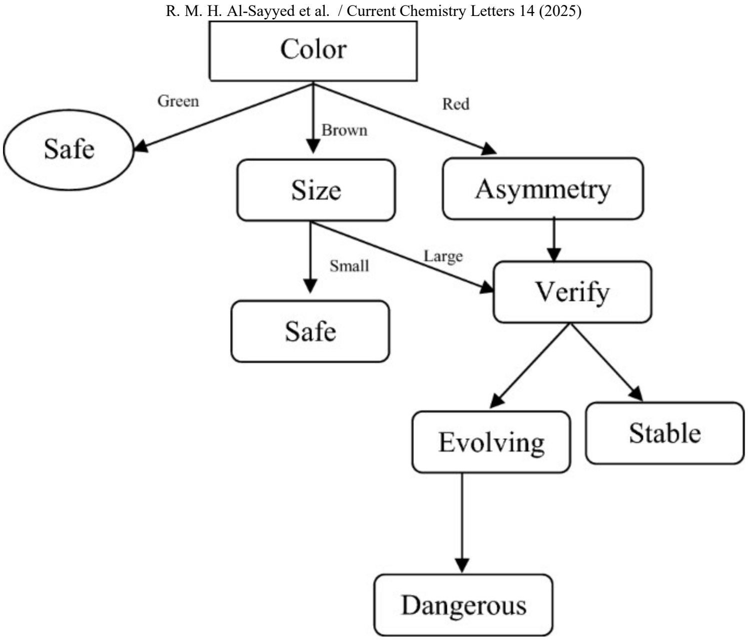

Fig. 7: Classification of skin lesions using decision trees and Random Forest algorithms[103]

Mazhar et al.[104]reviewed the application of ML and deep learning in dermatology, highlighting their role in assisting dermatologists from diagnosis to personalized care. Their comprehensive survey emphasized the importance of lesion segmentation and tracking in the development of effective skin cancer detection systems.

Using machine learning algorithms on datasets of skin conditions, Kaushal et al.[105] created a cloud-based mobile application for real-time skin cancer prediction. Their Näive Bayes-based model achieved high accuracy, demonstrating the practical applicability of ML in accessible diagnostic tools. Singh et al.[106] performed a comparative analysis of different convolutional neural networks (CNNs), including VGG16, InceptionV3, ResNet152V2, and a custom 12-layer CNN. Their results demonstrated how well deep learning architectures work to improve diagnostic precision for automated skin cancer diagnosis. With AUROCs of 0.67 and 0.71, respectively, Tighe et al.[107] demonstrated significant discriminating for basal cell carcinoma (BCC) and squamous cell carcinoma (SCC) when using machine learning (ML) models to evaluate surgical margins after curative surgery for non-melanoma skin cancer.

Table 5. The modality and method of different cancer deceases

Modality	Method	Remarks	Performance Metrics and Results	Ref.
Skin Cancer Segmentation	Hybrid Partial Differential Equation with Fuzzy Clustering	Feature extraction focus	97.7% accuracy using SVM	102
Melanoma Classification	Active Hybrid Machine Learning Technique	Enhanced accuracy through ensemble methods	Improved precision with majority voting	101
Skin Cancer Detection	ML and DL Approaches	Comprehensive survey	Insights into deep learning applications	104
Skin Cancer Prediction	Machine Learning and Cloud-Based Mobile App	Real-time application	96.61% accuracy with Naive Bayes	105
Skin Cancer Recognition	Comparative CNN Analysis	VGG16, InceptionV3, ResNet152V2	Improved diagnostic accuracy	106
Post-Surgery Audit	ML for Surgical Margin Prediction	Predictive modeling for BCC and SCC	AUROC = 0.67 for BCC, 0.71 for SCC	107
Skin Cancer Detection	Convolutional Kernel Extreme Learning Machine	Feature extraction with GLCM	98% accuracy	110
Skin Cancer Detection	OCT and Raman Spectroscopy Integration	High accuracy using dual modalities	85% accuracy overall, near 100% with Raman	108
Skin Cancer Detection	Single-Cell Transcriptomic Data Analysis	Insights into PD-1 blockade resistance	Identified distinct resistance mechanisms	73
Skin Cancer Prediction	Ensemble Machine Learning Techniques	Comparison of various ML models	85.02% accuracy with voting ensemble	109
Skin Cancer Diagnosis	Quantum ML for CAD	Performance comparison with classical methods	Emerging potential with quantum approaches	17
Skin Cancer Classification	Stacking Ensemble Approach	Combination of DL and ML methods	99.97% accuracy	111
Skin Cancer Classification	CNNs with Transfer Learning	Emphasis on high-quality datasets	Accuracy range: 85–95%	69
Skin Cancer Detection	Polarimetric Imaging and ML	Mueller matrix imaging Integration	94% accuracy with SVM	112
Skin Cancer Detection	CNNs with Transfer Learning	Focus on AI-based systems	Promising diagnostic outcomes	113

A technique for detecting skin cancer using the Convolutional Kernel Extreme Learning Machine (CKELM) was presented by Sarkar et al. in 2023. By combining Otsu's thresholding with the Grey-Level Co-occurrence Matrix (GLCM) for feature extraction, this method achieved 98% accuracy, outperforming conventional CNN and KELM techniques. In order to classify cells, You et al.[108] combined optical coherence tomography (OCT) with Raman spectroscopy, showing almost flawless accuracy when using Raman data. Their study highlighted the value of combining spatial and spectroscopic features to differentiate cancerous cells from normal ones. Liu et al.[73] utilized ML on single-cell transcriptomic data to reveal resistance mechanisms in skin cancer and pancreatic ductal adenocarcinoma (PDAC), providing insights into responses to immunotherapy. Duraisamy et al.[109] compared various ML algorithms, including XGBoost, Random Forest, and Logistic Regression, achieving 85.02% accuracy using a voting ensemble method, thereby emphasizing the potential of ensemble techniques in diagnostic tasks.

4. Deep Learning in Skin Cancer Detection

A specific type of machine learning called deep learning (DL) uses deep neural networks to find complex patterns in data. With the growth of large datasets and improvements in computational power, DL has become a key component in medical imaging, especially for skin cancer detection. The main ideas of deep learning (DL) are explained in this part, with an emphasis on CNNs and neural networks, which are essential for medical picture processing[114].

DL models extract hierarchical features from raw data by applying a series of transformations. At their core, the artificial neural networks that underpin these models were motivated by the architecture of the human brain. These networks are made up of linked nodes, or neurons, organized in three levels: input, output, and one or more hidden layers. Weighted connections connect the neurons, and iterative learning is used to modify the weights in order to enhance the model's predictions. This adjustment occurs via backpropagation, a technique that uses gradient descent to minimize errors, allowing the network to progressively refine its mapping of inputs to outputs[2, 115].

CNNs form of neural network designed specifically for image analysis tasks, such as skin cancer detection. CNNs incorporate convolutional and pooling layers, which enable efficient handling of image data's spatial structure[116].

Convolutional layers use filters (kernels) to process input images, creating feature maps that emphasize important characteristics like edges, textures, and patterns. These filters move across the image, performing element-wise multiplications to capture various features. As the image passes through successive convolutional layers, CNNs learn progressively more abstract and complex representations[117]. The feature maps are downsampled, or have their spatial dimensions reduced, via pooling layers, which are often positioned in between convolutional layers. This procedure improves the model's resilience to changes in the input data while reducing processing needs. The most popular pooling method, max pooling, chooses the greatest value from a specific area of the feature map[81].

In order to do classification or regression tasks, the last levels of a CNN are fully linked layers that combine the high-level information that were retrieved by previous layers. These layers provide probabilities that aid in the classification of skin lesions as either benign or malignant in the diagnosis of skin cancer[118].

Various CNN architectures have been developed to optimize performance for specific tasks. Early breakthroughs include AlexNet, which demonstrated the potential of deep CNNs in image classification, and VGGNet, which introduced smaller convolutional filters and deeper networks. Inception networks (e.g., GoogLeNet) used multi-scale filters to record information at different resolutions, and ResNet fixed the vanishing gradient issue in deep neural networks by including residual connections[119].

CNNs have achieved remarkable success in analyzing dermoscopic images, which provide detailed views of skin lesions. By training CNNs on extensive datasets of labeled dermoscopic images, these networks can distinguish subtle differences between benign and malignant lesions, significantly improving diagnostic accuracy. Training involves preprocessing the images (e.g., normalization and augmentation) to enhance data quality and diversity, followed by iterative weight optimization to minimize classification errors. Once trained, CNNs can classify new images, offering valuable diagnostic support to clinicians[19, 120].

4.1 DL Architectures for Skin Cancer Detection

Deep learning architectures have become indispensable in skin cancer detection, driving advancements in diagnostic precision and efficiency, as illustrated in **Fig. 8**. These architectures autonomously learn meaningful features from complex datasets, making them ideally suited for medical image analysis.

Convolutional Neural Networks (CNNs) remain the most prominent DL architecture for skin cancer detection. CNNs excel in capturing spatial hierarchies of features through convolutional and pooling layers. While activation functions like Rectified Linear Units (ReLU) offer non-linearity to describe complex patterns, convolutional layers capture elements like edges, textures, and colors. By decreasing the size of feature maps, pooling layers preserve important data while lowering computational complexity. Using CNNs' hierarchical learning structure, fully linked layers combine these characteristics to categorize lesions as benign or malignant[116].

Transfer learning is another impactful technique in DL applications for skin cancer detection. This approach uses pre-trained models, such as VGGNet, ResNet, or InceptionNet, trained on large datasets like ImageNet, to perform specialized tasks with smaller datasets. By replacing the final classification layer with one tailored to skin lesion categories, transfer learning enables models to utilize previously learned features while adapting to new tasks. Freezing earlier layers ensures retention of general features, while newly added layers are trained on the target dataset, reducing training time and data requirements while enhancing performance[119].

Ensemble learning improves performance and reliability by combining the results of several models. The drawbacks of individual models are addressed by combining predictions using techniques like bagging, boosting, and stacking. While boosting trains models sequentially, with each new model aiming to rectify the mistakes of the preceding ones, bagging trains many models on distinct subsets of the data and combines their predictions by averaging. Stacking creates a more reliable and accurate diagnostic system by efficiently combining the predictions of base models using a meta-model[121].

Attention mechanisms have further enhanced DL architectures, improving both accuracy and interpretability. These mechanisms focus on the most relevant image regions, highlighting areas indicative of skin cancer. Advanced architectures, such as Transformer models, which rely on attention mechanisms, have demonstrated effectiveness in capturing long-range dependencies in data and analyzing complex image features, making them suitable for nuanced diagnostic tasks in skin cancer detection.

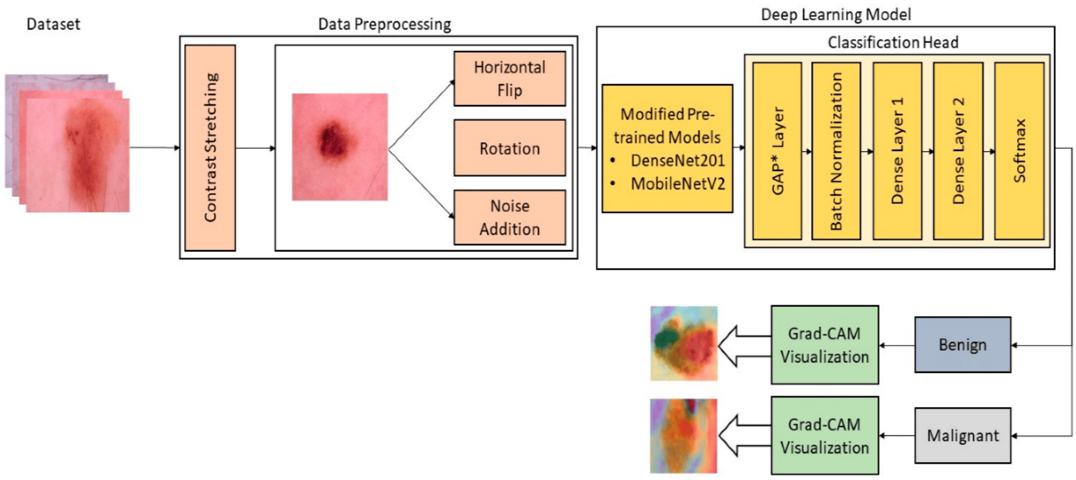

Fig. 8: Classification of Skin Cancer Lesions Using Deep Learning[121]

4.2 Dataset and Training

The effectiveness of DL models in detecting skin cancer is strongly influenced by the quality and volume of datasets, as well as the rigor of the training processes. Well-known datasets like the archive of International Skin Imaging Collaboration (ISIC) and HAM10000 have significantly contributed to this field by providing large collections of annotated dermoscopic images. These datasets include a diverse array of skin lesion types diagnosed by expert dermatologists. The ISIC archive, one of the most extensive publicly available repositories, aggregates images from numerous international sources, each accompanied by meticulous annotations essential for supervised learning. Similarly, the HAM10000 dataset comprises 10,015 dermoscopic images, capturing a wide spectrum of lesion types to ensure model generalizability across various skin conditions and demographics.

Before training, these images are preprocessed to improve quality and standardize inputs. The preprocessing steps involve resizing the images to consistent dimensions, facilitating batch processing and reducing computational demands. Pixel normalization scales the data uniformly, expediting convergence during training. Data augmentation techniques—such as flipping, rotation, color alterations, and cropping—artificially increase the dataset size, helping models learn invariant features and improving robustness and generalization capabilities.

The dataset is frequently divided into three subsets throughout the training process: test, validation, and training sets. The model is trained using the training set, which enables it to recognize characteristics and patterns in the photos. By evaluating performance on unseen data during training, the validation set adjusts hyperparameters and avoids overfitting. The model's objective performance is assessed using the test set, which is maintained apart from the training phase to guarantee that it can generalize to new, untested datasets.

CNNs' outstanding image processing capabilities make them the most popular architecture for skin cancer diagnosis. A CNN is made up of fully connected layers that do classification, pooling layers that shrink the spatial size of the input, and convolutional layers that detect spatial characteristics. CNNs' layered architecture enables progressive learning, with deeper layers collecting more intricate, abstract patterns and early levels concentrating on basic properties.

Transfer learning has become a common method for improving deep learning models' performance, particularly when data is scarce. It entails using pre-trained models that have been learned on large datasets like ImageNet, such as VGGNet, ResNet, or InceptionNet. These pre-trained models capture robust, generalizable features that can be fine-tuned for specific datasets, like those with skin lesions, leading to substantial performance improvements and reduced training time. Regularization methods are critical for preventing overfitting and improving generalization. In order to encourage the model to create redundant representations and increase its resilience, dropout is a technique that randomly disables a portion of neurons during training. By normalizing the inputs inside each layer and assisting in the reduction of internal covariate changes, batch normalization increases training speed and stability.

To guarantee diagnostic reliability, model performance is evaluated using a number of measures. While sensitivity (also known as recall) gauges the model's capacity to accurately detect malignant lesions, accuracy assesses the total percentage of accurate predictions. Specificity evaluates how well benign lesions are identified. A comprehensive scalar statistic for assessing performance across different categorization thresholds is provided by the area under the receiver operating characteristic curve (AUC-ROC). When taken as a whole, these indicators offer a comprehensive evaluation of the diagnostic accuracy of the model.

By utilizing high-quality datasets, rigorous preprocessing, robust training methods, and advanced architectures such as CNNs enhanced with transfer learning and regularization, DL models achieve exceptional accuracy and efficiency. These advancements support improved clinical outcomes by delivering reliable and accurate diagnostic tools.

4.3 Performance Metrics

Evaluating the performance of deep learning models in skin cancer detection requires the use of thorough metrics to assess their diagnostic reliability in clinical settings. These metrics are essential for determining the model's ability to provide accurate and trustworthy detection results.

Accuracy evaluates the ratio of correctly classified samples to the total number of samples, providing a general assessment of the model's performance. However, accuracy may be misleading in cases of imbalanced datasets, where benign lesions significantly outnumber malignant ones.

Sensitivity, or recall, evaluates the proportion of actual malignant lesions correctly identified, reflecting the model's ability to detect cancerous lesions. Conversely, specificity measures the proportion of benign lesions correctly classified, indicating the model's effectiveness in avoiding false positives. High sensitivity ensures malignant lesions are not missed, while high specificity reduces unnecessary medical interventions. Precision measures the proportion of true positives among all predicted positives, which is especially crucial in clinical settings to minimize the occurrence of false positives. The F1 score, which is the harmonic mean of precision and recall, combines both false positives and false negatives into a single metric, providing a balanced evaluation.

The trade-off between sensitivity and specificity across various thresholds is represented by the Receiver Operating Characteristic (ROC) curve. The AUC-ROC provides a single measure summarizing performance, where values close to 1 indicate superior model accuracy. AUC-ROC is particularly valuable for comparing multiple models.

Confusion matrices offer a detailed breakdown by showing the counts of true positives, true negatives, false positives, and false negatives. These matrices identify areas where the model may be underperforming, guiding targeted improvements.

Additional metrics like Negative Predictive Value (NPV) and Positive Predictive Value (PPV) provide probabilities of correctness for negative and positive predictions, respectively, enhancing reliability in clinical contexts. The Matthews Correlation Coefficient (MCC) accounts for all confusion matrix quadrants, offering a balanced measure of performance, especially for imbalanced datasets.

4.4 Challenges and Limitations

Despite their promise, deep learning models for detecting skin cancer encounter various challenges and limitations. One primary challenge is the scarcity of high-quality annotated datasets. The creation of such datasets requires expert dermatological input, which is both time-intensive and costly. Variability in imaging conditions, including lighting and resolution, further complicates the consistency required for robust model performance. Class imbalance, where benign lesions outnumber malignant ones, introduces bias, reducing sensitivity to malignancies. While techniques like data augmentation and weighted loss functions help, they are not definitive solutions. The interpretability of deep learning models continues to be a significant limitation. Complex architectures often function as "black boxes," limiting transparency in decision-making. This lack of explainability can hinder acceptance in clinical environments. Research into interpretability techniques, such as saliency maps and attention mechanisms, aims to address this issue.

Generalization across diverse clinical environments is challenging. Variations in skin types, imaging conditions, and lesion characteristics affect model performance. Extensive validation on diverse datasets is necessary but often difficult to achieve.

Regulatory and ethical concerns, including compliance with healthcare regulations like HIPAA and ensuring data security, are critical considerations. Additionally, the responsibility for AI-driven diagnostic errors raises ethical questions about accountability in clinical practice.

The computational demands of training DL models present another limitation. Deep neural networks require substantial resources, including high-performance GPUs, which may not be accessible to all institutions.

Finally, integrating DL models into existing clinical workflows requires technical compatibility and user-friendly interfaces. Continuous learning to adapt models to new data and evolving medical knowledge adds further complexity.

Tackling these challenges is essential for the broader adoption of DL models in skin cancer detection, ensuring they deliver accurate, reliable, and ethically sound diagnostic support.

4.5 Related Work

The combination of ML and DL techniques has driven notable advancements in skin cancer detection and classification. Diverse methodologies have been proposed to enhance diagnostic accuracy and operational efficiency in this critical domain.

In 2024, Al-Rakhami et al.[36] created a federated learning-based skin cancer diagnostic system that incorporates deep convolutional neural networks (DCNNs). This method effectively addressed data privacy concerns by enabling collaborative learning without direct data sharing, achieving high diagnostic accuracy across multiple datasets and underscoring its potential to support dermatological decision-making.

Hossain et al.[122] proposed an innovative method that combines advanced pre-trained deep learning models using a Max Voting Ensemble technique. By using models like VGG16, MobileNetV2, ResNet50, and AlexNet, their approach achieved a diagnostic accuracy of 93.18% on the ISIC 2018 dataset, highlighting the effectiveness of ensemble learning in improving model performance.

Mazhar et al.[104] provided a review of ML and DL applications in dermatology. Their study highlighted the utility of these technologies in tasks ranging from diagnosis to personalized care, emphasizing the importance of full lesion segmentation and tracking to develop robust skin cancer detection systems.

Murugan et al.[43] employed transfer learning and dropout techniques for multi-class skin lesion classification using Convolutional Neural Networks (CNNs). Their model achieved an accuracy of 90% on the ISIC dataset, with the study exploring practical applications such as cloud-based solutions and API deployment for clinical use.

Zhang et al.[32] presented a deep learning system that makes use of an improved Orca Predation Algorithm (OPA) and Gated Recurrent Unit (GRU) networks. This technique demonstrated improved overall accuracy, sensitivity, and specificity, providing a viable means of detecting skin cancer early.

Shruthishree[123] developed an automated classification system leveraging deep transfer learning and dermoscopy. Their model achieved diagnostic accuracy comparable to expert dermatologists, underscoring its potential to reduce healthcare costs and improve early detection outcomes.

Pyun et al.[124] investigated the application of deep learning-based diagnostic algorithms in conjunction with laser-induced plasma spectroscopy (LIPS) for real-time, in vivo triage of skin cancer. Their system achieved high sensitivity (94.6%) and specificity (88.9%), demonstrating its effectiveness as a non-invasive diagnostic tool.

Subramanian et al.[125] utilized transfer learning with pre-trained architectural models to identify and classify malignant skin lesions. Tested on the ISIC dataset, their approach achieved 85% classification accuracy, illustrating the efficiency of transfer learning in reducing training requirements and enhancing model performance.

Bappi et al.[126] introduced the Mix Conv Dense GRU (MCD-GRU) model, which demonstrated exceptional accuracy rates of 99.90% during training and 99.13% during testing, highlighting its efficacy in classifying various skin cancer types.

Manju et al.[127] designed a computer-assisted detection system integrating 3D CNN with Inception V3 networks. Their model achieved high levels of accuracy (96%), sensitivity (97%), and specificity (97%), surpassing many state-of-the-art detection systems.

Table 6. The modality and methods

Modality	Method	Remarks	Performance Metrics and Results	Ref.
Skin Cancer Diagnosis	Federated Learning and Deep Convolutional Neural Networks	Privacy-preserving classification system	High accuracy across multiple datasets	36
Skin Cancer Detection	Max Voting Ensemble with Pre-Trained Models	Ensemble method combining multiple architectures	93.18% accuracy, 0.9320 AUC	122
Skin Cancer Detection	Deep Learning and Machine Learning Techniques	Comprehensive analysis of methodologies	Emphasis on segmentation and tracking	104
Skin Cancer Classification	CNNs with Transfer Learning	Multi-class classification using dropout integration	90% accuracy on ISIC dataset	43
Skin Cancer Detection	GRU Networks and Enhanced Orca Predation Algorithm	Optimized sequential learning approach	High sensitivity and specificity	21
Skin Cancer Detection	Deep Transfer Learning	Automated detection leveraging dermoscopy	Accuracy com parable to dermatologists	123
Skin Cancer Triage	LIPS and Deep Neural Networks	Non-invasive, real-time diagnostic system	94.6% sensitivity, 88.9% specificity	124
Skin Cancer Identification	Transfer Learning with Pre-Trained Models	Efficient classification using transfer learning	85% accuracy on ISIC dataset	125
Skin Cancer Detection	Mix Conv Dense GRU (MCD-GRU) Model	Robust model for skin cancer classification	99.13% testing accuracy	126
Skin Cancer Detection	3D CNN and Inception V3 Integration	Enhanced detection with advanced CNNs	96% accuracy, 97% sensitivity and specificity	127

5. Ethical and Legal Considerations

The rapid advancement of ML and DL technologies in skin cancer detection has introduced complex ethical and legal challenges. These challenges include potential biases in algorithmic decision-making, along with issues related to informed consent, data security, and patient privacy. Simultaneously, the evolving regulatory landscape for medical AI necessitates strict compliance to ensure high standards of patient care. This section examines the ethical dilemmas and legal frameworks associated with ML and DL in skin cancer detection, highlighting the responsibilities of researchers, developers, and healthcare providers in ensuring these technologies adhere to ethical principles and legal requirements.

5.1 Patient Privacy

Patient privacy remains a fundamental ethical consideration in deploying ML and DL technologies for skin cancer detection. The reliance on large datasets containing sensitive patient information for training and validating models underscores the importance of maintaining data confidentiality and compliance with legal standards.

In order to ensure patient privacy, anonymization and de-identification are essential processes. In order to prevent direct identification, anonymization involves removing personally identifying information (PII) from databases, such as names, addresses, and social security numbers. De-identification extends this protection by eliminating indirect identifiers, such as unique patient codes or demographic combinations, that could potentially trace data back to individuals. However, re-identification risks persist, particularly when datasets are cross-referenced with publicly available information.

Protecting data security is equally essential. Strong cybersecurity protocols are needed to protect both stored and transmitted data from unauthorized access, breaches, and leaks. These protocols involve using advanced encryption methods for data at rest and in transit, implementing access controls to restrict data usage to authorized personnel, and ensuring secure data-sharing practices. Ongoing security audits and compliance reviews are crucial for detecting and addressing potential vulnerabilities.

Informed consent is a fundamental principle of ethical data usage. Patients need to be completely informed about the ways in which their data will be used, including the objectives of data collection, associated risks, and the privacy measures implemented. Consent must be obtained transparently, ensuring patients understand their rights to withdraw consent at any stage without impacting their medical care. Simplifying the complexities of ML and DL technologies for laypersons is crucial for truly informed consent.

Data governance frameworks play an essential role in managing data responsibly. These frameworks define policies for data access, use, and sharing while ensuring compliance with ethical and legal standards. Research protocols should be supervised by institutional review boards (IRBs) or ethics committees to ensure that patient privacy is maintained throughout the data lifecycle.

It is essential to comply with laws like the General Data Protection Regulation (GDPR) in the European Union and the Health Insurance Portability and Accountability Act (HIPAA) in the United States. Strict guidelines for data protection and processing openness are enforced by HIPAA and GDPR. Serious legal and financial repercussions as well as harm to one's image may arise from noncompliance. Finally, maintaining transparency and accountability in ML and DL model usage is critical for building public trust. Organizations must clearly communicate the purposes and outcomes of data usage and the steps taken to protect privacy. Mechanisms for addressing privacy breaches and ethical violations, including reporting and grievance redressal systems, should be in place.

5.2 Regulatory Compliance

Regulatory compliance is a cornerstone of incorporating ML and DL technologies into healthcare, particularly in sensitive applications like skin cancer detection. Complying with legal and ethical standards is crucial to safeguarding patient rights, building public trust, and ensuring the effective and safe implementation of AI in clinical practice.

Strict guidelines are enforced by the Health Insurance Portability and Accountability Act (HIPAA) in the US to safeguard patient data. To guarantee the availability, integrity, and confidentiality of protected health information (PHI), HIPAA requires administrative, technological, and physical measures, including frequent risk assessments, secure data storage, and encryption. Serious consequences, like as fines and legal action, may follow noncompliance with HIPAA.

A comprehensive foundation for data privacy and protection is offered by the European Union's General Data Protection Regulation (GDPR). It is applicable to every organization, regardless of location, that manages the personal data of EU people. Core principles include data minimization, accuracy, and accountability. GDPR grants data subjects explicit rights, such as access to their data, the right to correct inaccuracies, and the right to request data erasure. Compliance for ML and DL applications involves rigorous anonymization, explicit patient consent, and robust data protection mechanisms.

Various regulatory bodies supervise the use of AI in healthcare. In the United States, the Food and Drug Administration (FDA) governs AI-driven diagnostic tools as medical devices. The FDA framework emphasizes safety, effectiveness, and transparency through premarket reviews and post-market surveillance. Similarly, the European Medicines Agency (EMA) mandates comprehensive clinical evidence for AI applications, emphasizing algorithmic transparency and explainability.

Ethical considerations are integral to regulatory compliance. Developers must ensure algorithms are free from biases and perform equitably across diverse demographic groups. This requires thorough testing, validation, and strict adherence to ethical standards, such as those set by the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems, which prioritize human well-being, fairness, and accountability.

5.3 Bias and Fairness

Bias and fairness are crucial ethical issues when applying ML and DL technologies in skin cancer detection. Bias in these systems can arise from multiple sources, such as algorithm design, training data, and outcomes interpretation. Addressing these biases is imperative to ensure equitable benefits of ML and DL technologies across diverse patient demographics.

A primary source of bias is the training data. If the dataset used to develop an ML model lacks representation of the population diversity intended for the system's application, the model may underperform for underrepresented groups. For instance, a dataset predominantly comprising images of skin lesions from lighter-skinned individuals may result in suboptimal diagnostic accuracy for darker-skinned patients. Such disparities can exacerbate existing healthcare inequalities. To mitigate this, training datasets must be diverse and inclusive, encompassing a wide spectrum of skin tones, ages, genders, and lesion types.

Algorithmic design also plays a significant role in introducing or amplifying biases. Decisions made during model development, such as selecting features or designing the neural network architecture, may unintentionally encode biases. To address this, researchers should thoroughly evaluate and refine these design choices, employing techniques like fairness aware ML, which integrates fairness constraints into the model training process, to develop more equitable systems.

The interpretation and utilization of results can further influence the perpetuation or mitigation of bias. Clinicians and healthcare providers must recognize that ML and DL models serve as decision-support tools rather than replacements for human judgment. Training healthcare professionals to critically evaluate AI outputs and remain vigilant about potential biases is essential. Additionally, transparently reporting model performance across diverse demographic groups can help identify and rectify disparities.

Ensuring fairness requires regular auditing and iterative updating of ML models. As new data emerges and population demographics evolve, continuous monitoring and retraining are necessary to preserve model accuracy and equity. Performance evaluations should include subgroup-specific analyses to ensure no demographic is disproportionately affected by the system's outputs.

Regulatory frameworks and ethical guidelines provide a structured basis for addressing bias and promoting fairness. Regulatory authorities such as the FDA and EMA mandate rigorous validation and safety assessments for ML and DL systems in healthcare. These evaluations often include specific requirements to identify and mitigate bias. Ethical frameworks, such as those offered by the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems, further emphasize principles of fairness, accountability, and human-centered AI development.

6. Conclusion

The integration of ML and DL technologies into the detection and diagnosis of skin cancer signifies a transformative advancement in dermatology. These innovative methods have demonstrated significant potential to enhance diagnostic accuracy, facilitate early detection, and streamline clinical workflows. By leveraging extensive datasets and sophisticated algorithms, ML and DL systems can discern subtle patterns in dermoscopic images that may elude human clinicians. This capability not only augments diagnostic processes but also holds promise for reducing missed diagnoses and improving patient outcomes through timely intervention.

Nonetheless, the successful deployment of these technologies requires addressing critical ethical, legal, and practical challenges. Respecting legal frameworks like HIPAA and GDPR, as well as protecting patient privacy and guaranteeing data security, are critical. Additionally, preventing the escalation of already-existing healthcare inequities requires minimizing biases in training data and guaranteeing equity in algorithmic judgments.

This section synthesizes the study's findings, highlighting the transformative benefits of ML and DL in skin cancer detection, including their precision in analyzing large datasets and their role in supporting clinical decision-making. It also underscores existing limitations, such as the dependence on extensive, diverse, and annotated datasets, the risk of algorithmic bias, and challenges related to integrating these technologies into current clinical workflows.

Future progress in this field should aim at creating more robust and interpretable models, improving data diversity and quality, and establishing comprehensive frameworks for ongoing monitoring and model updates. Collaboration among technologists, clinicians, and regulatory bodies will be essential to ensure that ML and DL technologies in dermatology remain innovative while adhering to ethical, transparent, and patient-centered principles. These technologies have the potential to transform the field of skin cancer diagnosis and treatment by providing safe, efficient, and fair healthcare solutions with further study and development.

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