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Review Article

Advancing skin cancer research with machine learning and deep learning models: A systematic review

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Abstract

Background The global impact of skin cancer has underscored the urgency of accurate and timely detection for effective treatment. In recent years, the medical research landscape has witnessed a rapid evolution fueled by the integration of Machine Learning (ML) and Deep Learning (DL) models, specifically aimed at enhancing skin cancer diagnosis and classification**.**

Methods This comprehensive exploration delves into the forefront of advancements, focusing on the strategic application of ML and DL algorithms across critical facets of skin cancer management, encompassing detection, classification, and prognosis. By synthesizing diverse studies and emerging developments, this review aims to provide an all-encompassing perspective of the current landscape in skin cancer research, underpinned by the capabilities of ML and DL models.

Results The synthesis of research outcomes within this review accentuates the remarkable progress achieved through the fusion of ML and DL methodologies. These achievements manifest as heightened accuracy and efficiency in skin cancer diagnosis and classification, offering invaluable support to healthcare professionals. The integration of these algorithmic approaches has ushered in improved patient outcomes, facilitating prompt interventions and tailored treatment strategies.

Conclusions At its core, this review strives to equip researchers, clinicians, and healthcare providers with an intricate comprehension of the existing terrain in skin cancer research, driven by the prowess of ML and DL models. By spotlighting accomplishments alongside untapped prospects for refinement, this endeavor seeks to inspire fresh breakthroughs in the domain of skin cancer detection.

Key words
Skin cancer diagnosis; Machine Learning (ML); Deep Learning (DL); Medical research; Early detection.

Introduction

Cancer represents a significant global health challenge, with incidence rates steadily increasing and potential severe consequences if detection and treatment are delayed.[1] Skin cancer, in particular, is a growing concern due to its rising prevalence, largely attributed to exposure to ultraviolet (UV) rays from the sun and other environmental factors.[2] Among the primary types of skin cancer are basal cell carcinoma, squamous cell carcinoma, and melanoma, all requiring precise classification to guide treatment decisions.[3]

This review seeks to furnish an extensive portrayal of the application of Artificial

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Intelligence (AI) and Machine Learning (ML) techniques in the classification of skin cancer.[4] In recent years, AI and ML have emerged as promising tools in supporting dermatologists and healthcare professionals with automated and reliable solutions for diagnostic purposes.[5]

AI techniques, particularly Deep Learning (DL) based on convolutional neural networks, have unlocked new opportunities to enhance early detection and diagnosis of skin cancer.[6] By conducting in-depth analysis of skin lesion images, AI can detect subtle patterns that may elude the human eye, thereby improving the accuracy of diagnostic outcomes.[7]

Throughout this review, we focus on the most promising approaches to skin cancer classification, critically evaluating their potential impact and effectiveness in clinical settings.

The goal is to shed light on the advancements in AI and ML techniques and their integration with skin cancer classification, contributing to the growing body of knowledge in this field.

The article is structured into several key sections, each addressing important aspects of skin cancer diagnosis:

Section 2 provides an in-depth analysis of the epidemiological aspects of skin cancer, exploring its prevalence, risk factors. Section 3 delves into various skin cancer variants, encompassing basal cell carcinoma, squamous cell carcinoma, and melanoma. It provides detailed descriptions of each subtype, along with their clinical characteristics. Section 4 focuses on the importance of datasets in skin cancer research and diagnosis. It examines the available datasets, their sources, and quality, gaining valuable insights into the diversity and size of the data used to train AI and ML models for skin cancer classification. Section 5 delves into the fascinating realm of AI methods applied in skin cancer diagnosis research. It explores various AI techniques, such as Machine Learning (ML) and Deep Learning (DL), along with their respective contributions to enhancing diagnostic accuracy and efficiency. The pivotal section 6 presents the research findings obtained from different studies focusing on skin cancer diagnosis. It conducts a critical analysis of the outcomes of research papers that have utilized Machine Learning (ML) techniques and those that have employed Deep Learning (DL) techniques. The final section 7 of the article provides an in-depth discussion and critical analysis of the presented research. It synthesizes the results and insights from previous sections, draws meaningful conclusions, and highlights the potential of AI methods in skin cancer diagnosis.

Epidemiology of skin cancer

This section provides an overview of the epidemiology of skin cancer, including risk factors, geographic trends, and affected demographics.

2.1 ***Factors associated with skin cancer development*** Skin cancer is influenced by several well-established risk factors **(Table 1)**, with the primary and most common one being exposure to ultraviolet (UV), radiation from the sun and artificial sources like tanning beds.[8] Prolonged and unprotected exposure to UV radiation can lead to DNA damage in skin cells, significantly increasing the risk of developing skin cancer. In addition to UV radiation, there are other significant risk factors that contribute to skin cancer susceptibility. Fair-skinned individuals, particularly those with lighter skin types, are more vulnerable to UV damage due to lower levels of melanin. Melanin acts as a natural shield against the sun's harmful effects, and individuals with fair skin have less of this protective pigment.[9] Furthermore, a family

Table 1 Risk Factors for Skin Cancer. [11]

Risk Factor	*Explanation*
Ultraviolet (UV) Radiation	Excessive sun exposure, tanning beds, and UV radiation
Fair Skin	Lighter skin types are more susceptible to UV damage
Family History	Previous cases of skin cancer in the family
Immune Suppression	Weakened immune system due to certain conditions
Age	Risk increases with age, especially in older adults
Personal History of Skin Cancer	Previous history of skin cancer increases risk
Precancerous Skin Lesions	Actinic keratosis and other precancerous conditions
Environmental Exposure	Exposure to certain chemicals or carcinogens

history of skin cancer plays a crucial role, indicating a genetic predisposition to the disease. Individuals with a family history of skin cancer face an elevated risk of developing the condition themselves. Weakened immune systems also contribute to increased skin cancer risk.[10] Immunosuppressed individuals, such as organ transplant recipients or those with certain medical conditions, have compromised abilities to detect and repair damaged skin cells, making them more susceptible to skin cancer. Age is another influential factor, with older adults facing higher risks. Accumulated UV exposure over a lifetime makes older individuals more prone to skin cancer development.[11] Moreover, a personal history of skin cancer or precancerous skin lesions can heighten the risk of future skin cancer occurrences. Furthermore, certain environmental exposures, such as those in specific industries, can contribute to skin cancer risk. Occupational exposure to specific chemicals or carcinogens, like arsenic or polycyclic aromatic hydrocarbons, may increase the likelihood of developing skin cancer in certain workers.[12]

2.2 *Geographic and Demographic Patterns of Skin Cancer* Skin cancer exhibits substantial variations in occurrence worldwide. In the year 2020, it was estimated that there were 325,000 new cases of melanoma globally, with 174,000 cases affecting males and 151,000 cases affecting females. Additionally, melanoma accounted for 57,000 deaths, with 32,000 deaths occurring in males and 25,000 deaths in females. Among various world regions, Australia/ New Zealand had the highest incidence rates, with 42 cases per 100,000 person-years in males and 31 cases per 100,000 person-years in females. Western Europe closely followed with rates of 19 per 100,000 person-years for both genders. North America recorded 18 cases per 100,000 person-years in males and 14 cases per 100,000 person-years in females, while Northern Europe reported 17 cases per 100,000 person-years in males and 18 cases per 100,000 person-years in females. In contrast, melanoma remained relatively uncommon in the majority of African and Asian nations, usually with incidence rates below 1 per 100,000 person-years.[13]

Cancer incidence rates can vary based on geographic regions and demographic factors. Notably, higher incidence rates are often observed in regions with elevated UV radiation and sunny climates. Geographically, regions closer to the equator tend to have higher rates of skin cancer compared to more polar regions.[14] As evident in countries with sunny climates like Australia and New Zealand, higher incidences of skin cancer are commonly reported. Demographically, there are notable differences in skin cancer incidence based on age and gender. Older adults are more susceptible to skin cancer, likely due to cumulative UV exposure over their lifetimes. Moreover, males tend to exhibit higher rates of skin cancer compared to females, possibly because they are more likely to engage in outdoor activities without adequate sun protection.[15] To gain a comprehensive

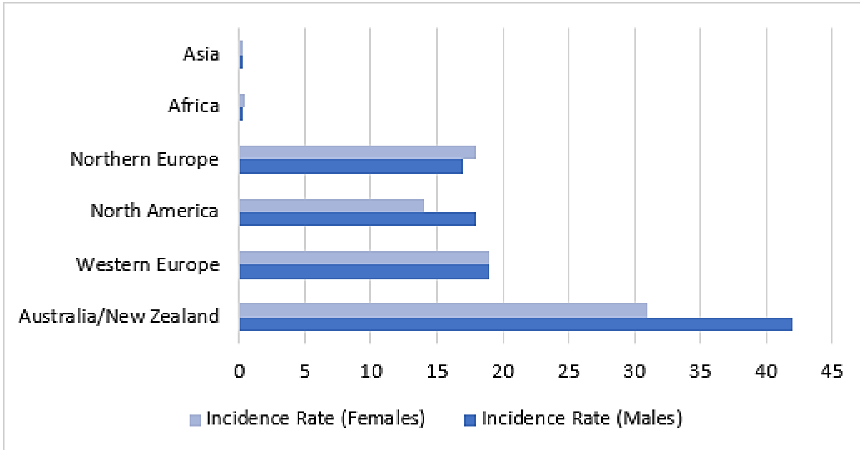

Figure 1 Skin Cancer Incidence Rates by World Regions (per 100,000 person-years).[13]

Figure 2 Basal Cell Carcinoma images.[17]

overview of skin cancer incidence rates across different world regions, please refer to **Figure 1**.

Types of Skin Cancer

Skin cancer encompasses various types, each with unique characteristics and degrees of severity.

3.1 *Basal Cell Carcinoma (BCC)* BCC is the most frequently occurring type of skin cancer. It commonly presents as a small, smooth, and shiny bump with a pink or red hue. The slow growth rate of this cancer contributes to its rarity of metastasis to other body parts, rendering it highly treatable if detected early.[16,17] **Figure 2** illustrates some of this type.

3.2 *Squamous Cell Carcinoma (SCC)* Following BCC, SCC emerges as the second most prevalent form of skin cancer. This variant usually appears as a firm, red nodule or a crusty, scaly growth. Unlike BCC, SCC has a higher propensity to spread to nearby tissues, underscoring the importance of early detection and prompt treatment.[18] **Figure 3** illustrates examples of this particular skin cancer type.

3.3 *Melanoma* Although less common than BCC and SCC, melanoma is the most dangerous

Figure 3 Examples of Squamous Cell Carcinoma images.[18]

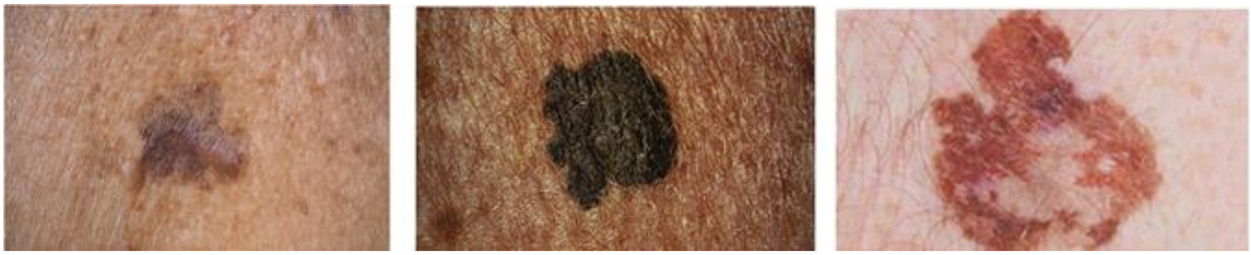

Figure 4 Examples of Melanoma images.[19]

Figure 5 Merkel Cell Carcinoma images.[20]

form of skin cancer. It originates from melanocytes, the cells responsible for producing melanin, which gives color to the skin. Melanoma can appear as a new mole or a change in an existing mole, exhibiting irregular shapes, colors, and sizes. Early detection is critical, as melanoma can quickly spread to other parts of the body if left untreated.[19] **Figure 4** provides visual examples of this type of skin cancer.

3.4 ***Merkel Cell Carcinoma (MCC)*** MCC is an uncommon yet aggressive form of skin cancer. It usually manifests as firm, flesh-colored or bluish-red nodules on the skin. MCC grows rapidly and has a higher likelihood of metastasizing to other organs, necessitating prompt medical attention .[20] **Figure 5** showcases examples of this skin cancer type.

3.5 ***Kaposi Sarcoma (KS)*** KS[21] is a relatively rare form of skin cancer that predominantly affects individuals with compromised immune systems, such as those living with HIV/AIDS. It typically manifests as distinctive reddish or purple patches or nodules on the skin, and in some cases, it can involve the internal organs as well. **Figure 6** provides a visual representation of this particular skin cancer type.

3.6 ***Dermatofibrosarcoma Protuberans (DFSP)*** DFSP,[22] an uncommon form of skin cancer, is characterized by a raised, firm, and scar-like growth **(Figure 7)**. While it generally exhibits slow growth, DFSP can display local aggressiveness, necessitating surgical intervention for effective treatment.

3.7 ***Sebaceous Carcinoma*** Sebaceous carcinoma[23] represents an infrequent and highly aggressive form of skin cancer that initiates

Figure 6 Kaposi Sarcoma images.[21]

Figure 7 Dermatofibrosarcoma Protuberans images.[22]

Figure 8 Sebaceous Carcinoma images.[23]

within the skin's oil glands. It typically manifests as a painless, slow-growing nodule or a yellowish lump, as depicted in **Figure 8**. This type of skin cancer requires prompt attention and accurate diagnosis due to its aggressive nature. Early detection and appropriate treatment are crucial in managing sebaceous carcinoma effectively and improving the chances of successful outcomes.

3.8 ***Adnexal Carcinoma*** Adnexal carcinoma[24] is a seldom-encountered skin cancer that originates from the hair follicles, sweat glands, or sebaceous glands. This type of cancer can present in diverse forms, including nodules, cysts, or ulcers **(Figure 9)**.

Datasets used in skin cancer research

The availability of diverse and comprehensive datasets has been instrumental in the advancement of skin cancer research. Valuable resources, these datasets facilitate the training and evaluation of machine learning or deep learning models, aid in the development of diagnostic algorithms, and provide deeper insights into various aspects of skin cancer. This section offers an overview of prominent datasets commonly utilized in skin cancer research.

1. ISIC Archive [25]: This widely used dataset contains over 23,000 high-quality skin images, encompassing a range of benign and malignant skin lesions. It serves as a benchmark dataset for developing automated skin cancer classification systems.
2. HAM10000 [26]: The HAM10000 dataset encompasses 10,015 dermoscopic images collected from various sources, featuring seven different types of skin lesions. Researchers often use it for tasks such as lesion segmentation and classification.

Figure 9 Images of Adnexal Carcinoma.[24]

3. PH[2] [27]: With 200 dermoscopic images accompanied by clinical information and lesion segmentation metadata, the PH2 dataset is particularly valuable for research involving melanocytic lesion analysis.
4. SD-198 [28]: The SD-198 dataset is a multi-modal collection of 6,584 skin lesion images, featuring both dermoscopic and clinical images. Its coverage of various skin lesion types makes it a diverse resource for research purposes.
5. Dermofit Image Library [29]: Dermofit offers a collection of clinical and dermoscopic images, totaling over 1300 images. Its wide range of skin conditions makes it a valuable resource for dermatological research.
6. SONIC [30]: The SONIC dataset includes 2000 dermoscopic images with corresponding segmentations, serving as a valuable resource for research in skin lesion segmentation and boundary detection.
7. BCN20000 [31]: Covering melanocytic and non-melanocytic lesions, the BCN20000 dataset contains 19,424 images from the Hospital Clínic de Barcelona.
8. MED-NODE [32]: consisting of 170 skin lesion images, MED-NODE is specifically curated for skin lesion classification tasks.

Table 2 presents a concise overview of these datasets, encompassing their descriptions, sizes, and classes.

AI methods in skin cancer diagnosis research

Artificial Intelligence (AI)[33] has revolutionized various aspects of healthcare, offering innovative solutions to complex medical challenges. In the arena of skin cancer diagnosis and research, AI has emerged as a powerful tool, aiding healthcare professionals in improving accuracy, efficiency, and patient outcomes.[34]

AI-driven applications in healthcare encompass a wide range of techniques,[35] with machine learning and deep learning being prominent areas of focus.[36] Machine learning algorithms, such as Support Vector Machines (SVM),[37] Random Forests,[38] and Decision Trees,[39] have been extensively employed in skin cancer diagnosis. These algorithms can analyze vast amounts of data, learn patterns, and make predictions, enabling early detection and accurate classification of skin lesions.

Table 2 Summary of datasets used in skin cancer research.

Dataset Name	*Description*	*Size*	*Classes*
ISIC Archive[25]	high-quality skin images	>23000	Benign, Malignant
HAM10000[26]	Dermoscopic images with seven different skin lesion types	10015	Melanocytic Nevus, Melanoma, Benign Keratosis, Basal Cell Carcinoma, Actinic Keratosis, Vascular Lesion, Dermatofibroma
PH[27]	200 dermoscopic images with metadata	200	Melanocytic Nevus, Melanoma
SD-198[28]	Multi-modal collection of 6584 skin lesion images	6584	Various skin lesion types (198 classes)
Dermofit Image Library[29]	Clinical and dermoscopic images	>1300	Dermofit Image Library
SONIC[30]	Dermoscopic images with segmentations	2000	Benign, Malignant
BCN20000[31]	19424 images from Hospital Clínic de Barcelona	19424	Nevus, Melanoma, Basal Cell Carcinoma, Seborrheic Keratosis, Actinic Keratosis, Squamous Cell Carcinoma, Dermatofibroma, Vascular Lesion
MED-NODE[32]	170 skin lesion images specifically curated for classification tasks	170	Melanocytic, Non-melanocytic

Deep Learning methods have gained substantial popularity for their ability to process and interpret high-dimensional data, such as medical images, with remarkable accuracy. Convolutional Neural Networks (CNN)[40] are at the forefront of AI-driven skin cancer diagnosis, as they excel in image recognition and feature extraction. Transfer learning,[41] another deep learning technique, allows leveraging pre-trained models on large datasets to enhance performance even with limited data.

Generative Adversarial Networks (GANs)[42] have also found application in the domain of skin cancer research, particularly in image synthesis and augmentation. GANs can generate synthetic images that closely resemble real skin lesions, aiding in data augmentation and improving the robustness of AI models.[43]

AI-driven tools for skin lesion classification and segmentation have shown immense promise. These tools can automatically identify and delineate suspicious regions, streamlining the diagnostic process and reducing human error 44.

Furthermore, Case-Based Reasoning (CBR) systems[45] have also been utilized in skin cancer diagnosis. CBR capitalizes on past cases and experiences to furnish solutions for new, similar cases. In the context of skin cancer, CBR systems possess the capability to juxtapose novel patient data with an archive of previously established cases, thereby providing precise and individualized diagnoses along with tailored recommendations for treatment.

Nevertheless, it is essential to acknowledge the obstacles and restrictions of AI in skin cancer detection. The reliance on vast amounts of high-quality data, potential biases in training data, and interpretability issues are areas that researchers continue to address.[34]

5.1 *Advantages and limitations of AI in skin cancer detection* Within this section, an exploration of the advantages and limitations of AI in the realm of skin cancer detection is undertaken.

5.1.1 Advantages of AI in skin cancer detectionAmong the advantages of AI in the field of skin cancer detection are the following:

1. AI-driven algorithms, including machine learning and deep learning models, have exhibited heightened precision in identifying skin cancer as opposed to conventional techniques. These models possess the capability to analyze extensive datasets and uncover nuanced patterns that might escape human observation, ultimately resulting in enhanced accuracy in early and precise diagnoses.[46]
2. AI-based tools can process medical images and patient data quickly, allowing for faster and more efficient diagnosis. This can significantly reduce the time taken for patients to receive their results and initiate appropriate treatment plans.[47]
3. AI can aid in personalized medicine by analyzing individual patient data and medical history to provide tailored diagnoses and treatment recommendations. This approach can lead to more effective and targeted interventions for patients.[48]
4. Deep learning models, such as neural networks, can continuously learn and improve their performance as they are exposed to more data. This adaptability enables AI systems to stay up-to-date with evolving medical knowledge and improve over time.[49]

5.1.2 Limitations of AI in skin cancer detection Among the limitations of AI in the field of skin cancer detection are the following:

1. The precision and dependability of AI models rely significantly on the caliber and variety of the training data. Biased or insufficient datasets can result in prejudiced or erroneous forecasts, underscoring the significance of meticulous data collection and curation.[50]
2. Deep learning models, such as convolutional neural networks, are frequently referred to as "black boxes" due to their intricate architectures and opaqueness in decision-making processes. The inability to interpret the underlying reasoning behind AI-generated predictions may raise concerns in the medical community and limit their widespread adoption.[51]
3. AI models may encounter a challenge known as over fitting, wherein they exhibit outstanding performance on the training data, yet encounter difficulty when attempting to apply this learning to novel, unseen data.[52]
4. Despite the advancements in AI, there may be resistance to the widespread clinical adoption of AI-driven tools. Healthcare professionals may be cautious about fully relying on AI for critical decisions, preferring a combination of AI and human expertise in the diagnostic process.[53]
5. AI applications in healthcare raise ethical and legal concerns, such as patient privacy, data security, and liability in case of errors or misdiagnoses.[54]

Results

This section presents a comprehensive summary of the research papers on skin lesion classification gathered from the literature. The investigation involved meticulous examination and categorization of these papers based on the techniques employed in skin cancer detection.

6.1 ***Papers Utilizing Machine Learning (ML) Techniques*** In a study by Banasode P *et al*;[55] a machine learning technique, specifically Support Vector Machine (SVM), was employed for the detection of Melanoma skin cancer. The results obtained from this research demonstrated promising performance metrics, with a sensitivity of 95.7%, specificity of 90.2%, and an overall accuracy of 96.9%. The dataset utilized in this investigation was obtained from the ISIC (International Skin Imaging Collaboration) and comprised a collection of more than 5341 images, including cases of both melanoma and non-melanoma skin lesions.

In the study by Balaji V *et al*;[56] the primary objective was to devise an effective strategy for the segmentation of skin lesions and the classification of associated diseases. A unique dynamic graph cut algorithm was employed for precise skin lesion segmentation. For evaluation, the researchers employed the ISIC 2017 dataset, a compilation of diverse skin images, to validate their proposed technique. To achieve skin disease classification, they implemented the Naïve Bayes classifier,[57] a probabilistic approach. Notably, the method attained impressive accuracies of 94.3% for benign cases, 91.2% for melanoma, and 92.9% for keratosis, underscoring its potential in propelling the realms of skin disease diagnosis and treatment forward.

Ahammed M *et al*;[58] presented an innovative technique for digital hair removal, employing morphological filtering encompassing Black-Hat transformation and inpainting algorithms, alongside Gaussian filtering. The objective was to enhance image clarity and diminish noise in skin images. The authors further integrated the automatic Grabcut segmentation technique to precisely outline affected skin lesions. In order to extract meaningful patterns from these skin images, the study employed the Gray Level Co-occurrence Matrix (GLCM) and statistical feature methodologies. The evaluation of skin image classification follows, wherein three machine learning methods Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) classifiers undergo comprehensive assessment. These classifiers leverage the extracted features to effectively categorize distinct skin conditions including melanoma (MEL), melanocytic nevus (NV), basal cell carcinoma (BCC), actinic keratosis (AK), benign keratosis (BKL), dermatofibroma (DF), vascular lesion (VASC), and squamous cell carcinoma (SCC). The models exhibit exceptional accuracy, with SVM notably surpassing the other classifiers. It attained impressive scores of 95%, 94%, and 93% on the ISIC-2019 dataset, and 97%, 95%, and 95% on the HAM10000 dataset, respectively.

In another study by Sinthura SS *et al*.[59] researchers introduced a robust methodology for precise identification of various skin diseases using image analysis. The approach involved noise reduction, grayscale conversion, and image segmentation to enhance image quality. Feature extraction reduced data processing, optimizing the classifier's analysis. The use of Support Vector Machine (SVM) in image classification achieved a remarkable 89% accuracy in detecting skin conditions like rosacea, melanoma, psoriasis, and acne.

In a study by Kanca E *et al*;[60] researchers proposed an innovative approach for binary image classification involving melanoma, nevus, and seborrheic keratosis. They employed the K-nearest neighbor (KNN) algorithm along with hand-crafted features like color, shape, and texture. These features were extracted from the publicly available ISIC 2017 dataset, comprising a diverse collection of skin region images. The study demonstrated the effectiveness of their method in accurately classifying these skin conditions based on the carefully selected features, offering valuable insights to enhance skin cancer diagnostic techniques. The evaluation yielded an accuracy of 68%, sensitivity of 80%, and specificity of 80%, indicating promising performance in distinguishing between these skin conditions.

Cheong KH *et al*.[61] introduced a groundbreaking Automated Skin-Melanoma Detection (ASMD) system, incorporating the concept of the Melanoma-Index (MI). The framework involves multiple stages, including image pre-processing, the application of Bi-dimensional Empirical Mode Decomposition (BEMD), texture enhancement, and the extraction of entropy and energy features. Subsequently, a binary classification process ensues, employing Support Vector Machine (SVM) and Radial Basis Function (RBF) algorithms. Impressively, the ASMD system achieved a classification accuracy exceeding 97.50% across a dataset of 600 benign and 600 malignant images.

Codella NC *et al*.[62] aimed to develop algorithms for automated melanoma diagnosis, with a particular focus on lesion segmentation, feature detection, and disease classification. The study yielded significant findings, showcasing the effectiveness of Linear SVM, which achieved an accuracy of 89.2%, sensitivity of 71.8%, and specificity of 90.1%. Additionally, Non-linear SVM showed promising results, with an accuracy of 85.3%, sensitivity of 67.5%, and specificity of 90.9%. The researchers utilized the ISIC2017 dataset, which served as a valuable resource for training and evaluating the algorithms in the study.

In a study by Janney BJ *et al*.[63] innovative image processing techniques were investigated for the purpose of detecting skin cancer using dermoscopy images. The investigators curated image samples of melanoma through the utilization of a dermoscope, followed by a meticulous segmentation process and subsequent feature extraction from the segmented images.

These extracted features were then input into three distinct classifiers: Support Vector Machine (SVM), Artificial Neural Network (ANN), and Naive Bayes. The outcomes revealed that the ANN exhibited an accuracy rate of 89%, sensitivity of 90%, and specificity of 88%. On the other hand, the Naive Bayes classifier demonstrated an accuracy of 71%, sensitivity of 90%, and specificity of 56%. Meanwhile, the SVM classifier achieved an accuracy rate of 71%, sensitivity of 70%, and specificity of 72%.

Sunitha G *et al*.[64] presented a highly efficient model designed for the classification of skin lesion imagery. They focus on fine-tuning hyperparameters using a political optimizer to create an optimized classifier. The performance of their proposed model was extensively evaluated using the ISIC-17 dataset, yielding impressive results. Specifically, the average accuracy, sensitivity, and specificity were reported as 97.86%, 97.36%, and 98.78%, respectively. Through a comprehensive comparative analysis, the authors demonstrate the superiority of their proposed classification model, which utilizes the political optimizer for hyper parameter tuning with XGBoost, outperforming SVM and BPN models.

Moussa R *et al.*[65] conducted a study focused on distinguishing between benign and malignant lesions using geometric features. They employed the k-Nearest Neighbors (k-NN) machine learning algorithm to classify 15 lesions based on their ABD features. Remarkably, the results demonstrated an impressive accuracy of 89% on the testing set of the DermIS dataset. The following **Table 3** provides a summary of these works.

6.2 Papers Employing Deep Learning (DL) Techniques In the study by Gulati S *et al*;[66] researchers devised a Computer-Aided

Table 3 Machine Learning Models for skin cancer detection in research papers.

Study	*Method*	*Dataset*	*Performance Metrics (%)*
55	Support Vector Machine (SVM)	ISIC archive	Accuracy: 96.9, Sensitivity: 95.7, Specificity: 90.2
56	Dynamic Graph Cut Algorithm, Naïve Bayes Classifier	ISIC 2017	Sensitivity: 94.3 (Benign), 91.2 (Melanoma), 92.9 (Keratosis),
58	Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbor (KNN)	ISIC 2019, HAM10000	Accuracy: 95 (ISIC-2019), 97 (HAM10000), Sensitivity: 94 (ISIC-2019), 95 (HAM10000), Specificity: 93 (ISIC-2019), 95 (HAM10000)
59	Support Vector Machine (SVM)	-	Accuracy: 89, Sensitivity: 90,
60	K-Nearest Neighbor (KNN)	ISIC 2017	Accuracy: 68, Sensitivity: 80, Specificity: 80
61	SVM, Radial Basis Function (RBF)	-	Accuracy: 97.50
62	Linear SVM, Non-linear SVM	ISIC 2017	Accuracy: 89.2 (Linear SVM), 85.3 (Non-linear SVM), Sensitivity: 71.8 (Linear SVM), 67.5 (Non-linear SVM), Specificity: 90.1 (Linear SVM), 90.9 (Non-linear SVM)
63	SVM, Artificial Neural Network (ANN), Naive Bayes	-	Accuracy: 89 (ANN), 71 (Naive Bayes), 71 (SVM), Sensitivity: 90 (ANN), 90 (Naive Bayes), 70 (SVM), Specificity: 88 (ANN), 56 (Naive Bayes), 72 (SVM)
64	Political Optimizer, XGBoost	ISIC 2017	Accuracy: 97.86, Sensitivity: 97.36, Specificity: 98.78
65	K-Nearest Neighbors	DermIS	Accuracy: 89

Diagnosis (CAD) system through the utilization of deep learning employing Convolutional Neural Networks (CNNs). They harnessed transfer learning and feature extraction methodologies using pre-trained networks, specifically AlexNet and VGG16. The outcomes revealed that the implementation of transfer learning with VGG16 attained the peak accuracy of 97.5%, accompanied by a sensitivity of 100% and a specificity of 96.87%.

In a study by Salido JAA *et al*;[67] researchers employed deep learning techniques for the automatic detection of melanomas in dermoscopy images. The initial step involved preprocessing the images to eliminate unwanted artifacts, such as hair, followed by an automatic skin lesion segmentation process. Subsequently, a convolutional neural network was utilized to classify the images. To assess the classifier's efficacy, it underwent testing using both preprocessed and unprocessed images from the PH^2 dataset. The findings demonstrated remarkable performance in terms of sensitivity, specificity, and accuracy. Specifically, their approach achieved an impressive 93% accuracy in identifying the presence or absence of melanoma, with sensitivities and specificities ranging from 86 to 94%.

In a study conducted by Roy SS *et al*;[68] they devised a real-time object detection method utilizing the YOLOv2 model for the automatic identification of melanoma in dermoscopic images. This approach yielded an accuracy of 86.00% in mole diagnosis, accompanied by a sensitivity of 86.35% and a specificity of 85.90%.

In the study by Hosny KM *et al*;[69] the authors developed an automatic skin lesion classification system using transfer learning and pre-trained deep neural networks. They fine-tuned the DCNN weights and applied various techniques, including replacing the classification layer and dataset augmentation. Their proposed method achieved impressive accuracy percentages: 96.86% for MED-NODE, 97.70% for Derm (IS & Quest), and 95.91% for ISIC.

In a study by Rodrigues DdA *et al*;[70] researchers introduced an IoT-based system that incorporated Transfer Learning and Deep Learning methodologies. This system was devised to assist medical professionals in the diagnosis of skin lesions. They leveraged various CNNs, including VGG, Inception, ResNet, Inception-ResNet, Xception, MobileNet, DenseNet, and NASNet, as resource extractors. Classifiers like Bayes, SVM, RF, MLP, and KNN were used for injury classification. The study employed the ISBI-ISIC and PH2 datasets, achieving impressive accuracies of 96.805% and 93.167%, respectively.

A two-stage framework utilizing Fully Convolutional Networks (FCNs) is suggested for automatic melanoma diagnosis.[71] The FCNs, based on VGG-16 and GoogLeNet, improve lesion segmentation accuracy. A hybrid framework combines their outputs. Features are extracted from segmented lesions using deep residual networks and hand-crafted features, and classification is performed using Support Vector Machine (SVM). The approach achieved a promising accuracy of 88.92% on the ISBI 2016 dataset and 85.3% on the ISIC 2017 dataset.

In a study by Albahar MA,[72] a novel prediction model was introduced to classify skin lesions into benign or malignant categories. This binary classifier achieved an impressive average accuracy of 97.49%, outperforming other state-of-the-art methods. The model was evaluated using Convolutional Neural Networks (CNN) and demonstrated favorable area under the curve (AUC) values for different lesion types: 77% for nevus against melanoma lesion, 93% for seborrheic keratosis versus basal cell carcinoma lesion, 85% for seborrheic keratosis versus melanoma lesion, and 86% for solar lentigo versus melanoma lesion.

Researchers proposed a convolutional neural network (CNN) for early-stage melanoma skin cancer detection.[73] They utilized 514 dermoscopic images from the ISIC archive for training and validation. Despite some challenges with image quality, the CNN achieved an accuracy of 74.76% and validation loss of 57.56%.

In another study by Ashraf R *et al*;[74] researchers developed an intelligent Region of Interest (ROI) based system for melanoma classification using transfer learning. The system employed an improved k-mean algorithm to extract ROIs from the images, focusing on discriminative features. By training the model solely on melanoma cell images, it achieved impressive accuracy rates of 97.9% and 97.4% on DermIS and DermQuest datasets, respectively.

Nida N *et al*.[75] proposed a deep learning method for automated Melanoma region segmentation using dermoscopic images. The method utilized a deep region-based Convolutional Neural Network (RCNN) along with Fuzzy C-mean clustering for localization. On the benchmark dataset ISIC-2016, their proposed approach achieved high specificity (94.17%), sensitivity (97.81%), and accuracy (94.8%) for Melanoma segmentation.

Wu Y *et al*;[76] improved a deep convolutional neural network (CNN) using transfer learning to classify 7 types of skin lesions from the ISIC 2017 HAM10000 dataset. They enhanced the original networks, including InceptionV3, ResNet50, and DenseNet201, by removing the output layer, adding new pooling and fully connected layers, and combining some existing layers. After fine-tuning the models, the improved ResNet50 achieved an accuracy of 86.69%, outperforming comparable methods by 3%.

In a study by Indraswari R *et al*;[77] a novel approach to classify melanoma images into benign and malignant categories using a deep learning model and transfer learning. The base model chosen for this research was MobileNetV2. Their proposed system achieved high accuracy, up to 85%, surpassing other networks.

The efficacy of deep features extracted from eight modern CNN models was examined in the context of melanoma detection by Gajera HK *et al*.[78] The research also delved into techniques involving boundary localization and normalization. The assessment, carried out on benchmark datasets including PH2, ISIC 2016, ISIC 2017, and HAM10000, revealed that the combination of DenseNet-121 with MLP yielded remarkable accuracy rates of 98.33%, 80.47%, 81.16%, and 81%, respectively. This performance surpassed that of other CNN models and even outperformed state-of-the-art methods.

Safdar K *et al*;[79] proposed an automated melanoma detection framework based on deep learning. They utilized standard skin lesion databases, including PH[2], Med-Node, and ISIC-2020, with extensive pre-processing to enhance image quality. The approach employed semantic segmentation using FCN-8 and an ensemble of deep ResNet-50 and Inception-V3 models for binary classification. The results showed impressive performance, with an accuracy of 94% for segmentation and an average accuracy of 93.4% for classification on augmented dermoscopy images.

Sharma P *et al*.[80] introduced a novel adversarial method that utilizes loss gradients with respect to input images to create new adversarial examples. These synthetic images are then used for training and testing the classification system. Their study includes a comparison between training with and without the adversarial approach, using pre-trained models such as VGG16, VGG19, Densenet121, and Resnet101. Notably, the results showed that ResNet101, trained with the adversarial approach, achieved a state-of-the-art accuracy of 84.77% for melanoma classification.

Gasmi S *et al*;[81] introduced a novel binary skin cancer classification approach using ensemble models based on pretrained CNNs, merging InceptionV3, VGG16, and EfficientNetB0. They employed 2637 dermoscopy images from the ISIC archive dataset, enhancing generalization with data augmentation to counter overfitting. The ensemble, including InceptionV3, VGG16, and EfficientNetB0, achieved a notable peak accuracy of 91.19% for distinguishing benign and malignant cases. In comparison, individual models achieved accuracies of 89.85%, 89.55%, and 90.87% (InceptionV3, VGG16, and EfficientNetB0 respectively), highlighting the superior performance of the ensemble, particularly InceptionV3+VGG16+EfficientNetB0, in precise skin cancer diagnosis.

Gasmi S *et al*;[82] investigated data augmentation's impact on training the InceptionV3 model for binary skin cancer image classification using the ISIC archive dataset. They introduced three augmentation techniques: offline, online, and a combined approach. Through systematic experiments, their study gauged the InceptionV3 model's performance with each augmentation method. Offline augmentation yielded 67.42% accuracy, while online augmentation achieved 90% accuracy emphasizing its efficacy. The hybrid approach combining offline and online techniques resulted in 88.76% accuracy. The following **Table 4** provides a summary of Deep Learning Models in Skin Cancer Detection Studies.

Discussion

Skin cancer poses a significant threat, emphasizing the criticality of early and precise diagnosis for effective treatment and better patient outcomes. However, the manual diagnosis by dermatologists can be a laborious and intricate process. In this regard, Computer-Aided Diagnosis (CAD) systems emerge as a promising solution, enabling faster and more accurate assessments. These CAD systems hold the potential to revolutionize skin cancer diagnosis, enhancing the overall efficiency of healthcare practices.

This systematic review of existing literature offers an extensive insight into the application of machine learning (ML) and deep learning (DL) methods within the scope of dermatology, with a specific focus on the detection and classification of skin lesions. The selected research articles encompass a wide range of ML and DL methodologies used for skin cancer detection, all of which have been evaluated using publicly available datasets to gauge their performance. By meticulously analyzing these studies, the review aims to illuminate the progress and possibilities presented by ML and DL methods in advancing the accuracy and efficacy of skin cancer diagnosis.

The analysis of the research papers indicates that Support Vector Machine (SVM) stands out as the most commonly used machine learning (ML) classifier in skin cancer detection studies, as illustrated in **Figure 10**. Additionally, **Figure 11** demonstrates that convolutional neural networks (CNNs) are the prevailing choice among deep learning (DL) models. The remarkable potential

Table 4 Summary of Deep Learning Models in skin cancer detection studies.

Study	*Method*	*Dataset*	*Performance Metrics (%)*
66	CNN (Convolutional Neural Networks)	PH^2	Accuracy: 97.5, Sensitivity: 100, Specificity: 96.87
67	CNN (Convolutional Neural Network)	PH^2	Accuracy: 93, Sensitivity: 86-94, Specificity: 86-94
68	YOLOv2 (You Only Look Once v2)	PH^2	Accuracy: 86.00, Sensitivity: 86.35, Specificity: 85.90
69	Transfer Learning, Deep Neural Networks	Med-Node, Derm (IS & Quest), ISIC 2017	Accuracy: 96.86 (MED-NODE), 97.70 (Derm), 95.91 (ISIC)
70	Transfer Learning, Deep Learning (Various CNNs)	ISBI-ISIC, PH^2	Accuracy: 96.805 (ISBI-ISIC), 93.167 (PH2)
71	FCNs (Fully Convolutional Networks), SVM	ISBI 2016, ISIC 2017	Accuracy: 88.92 (ISBI 2016), 85.3 (ISIC 2017)
72	Binary Classifier (CNN)	ISIC archive	Accuracy: 97.49
73	CNN (Convolutional Neural Network)	ISIC archive	Accuracy: 74.76, Validation Loss: 57.56
74	Transfer Learning (ROI-based System)	DermIS, DermQuest	Accuracy: 97.9 (DermIS), 97.4 (DermQuest)
75	Deep RCNN, Fuzzy C-mean clustering	ISIC 2016	Sensitivity: 97.81, Specificity: 94.17, Accuracy: 94.8
76	Transfer learning with improved CNNs	HAM10000	Accuracy: 86.69
77	Deep learning and transfer learning	ISIC archive	Accuracy: 85, Sensitivity : 85 Specificity : 85, Precision : 83
78	Deep features from CNN models	PH^2, ISIC 2016, SIC 2017, HAM10000	Accuracy: 98.33 (PH^2), Accuracy: 80.47 (ISIC 2016), Accuracy: 81.16 (ISIC 2017), Accuracy: 81 (HAM10000)
79	Ensemble of deep learning models	PH^2, Med-Node, ISIC 2020	Accuracy: 94 for Segmentation, Accuracy: 93.4 for Classification
80	Adversarial approach with pre-trained models	HAM10000	Accuracy: 84.77 (ResNet101)
81	Ensemble of deep learning models	ISIC archive	Accuracy: 91.19
82	InceptionV3 model	ISIC archive	Accuracy: 90

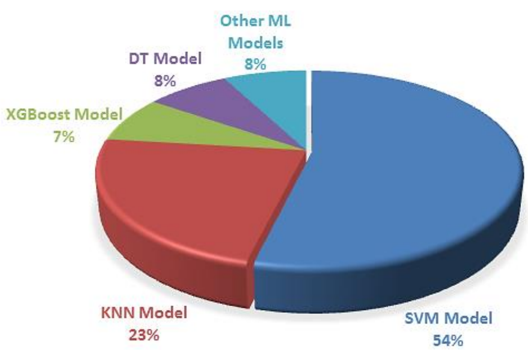

Figure 10 Utilized Machine Learning Models in studies for skin cancer detection.

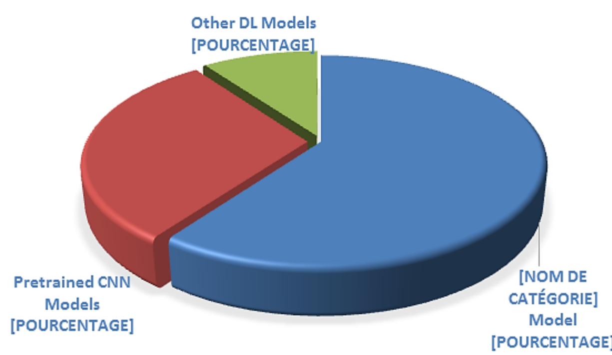

Figure 11 Utilized Deep Learning Models in studies for skin cancer detection.

of deep CNNs in enhancing the accuracy of skin lesion identification and classification makes them an exciting avenue for further research and holds promise for their application in clinical settings.

The analysis of datasets used in skin cancer classification studies reveals that the ISIC

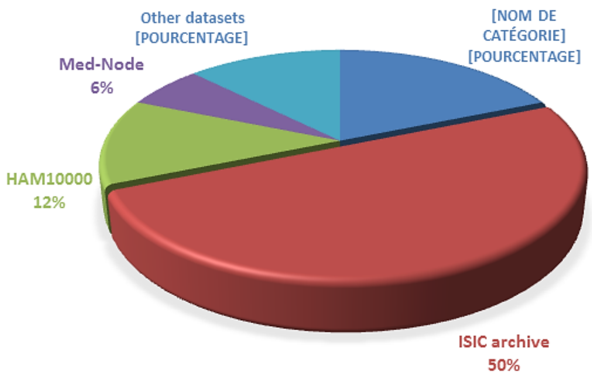

Figure 12 Overview of Utilized Datasets in Skin Cancer Classification Studies.

dataset and its variants, such as ISIC 2017 and ISIC Archive, are the most frequently employed datasets for training and testing machine learning and deep learning models. Additionally, the PH^2 dataset, HAM10000, and DermIS are also utilized in multiple studies **(Figure 12)**. Notably, the selection of public datasets allows for better comparison and evaluation of the model's performance across different research papers.

In conclusion, both machine learning and deep learning models show significant promise in skin lesion classification, displaying impressive accuracy in specific datasets. The review underscores the potential of CAD systems in advancing skin cancer diagnosis and highlights the ongoing need for further research in this crucial medical field.

Conclusion

This comprehensive study highlights the significant promise of machine learning and deep learning models in the field of skin lesion classification. These models have demonstrated impressive accuracy, particularly when applied to specific datasets, thereby paving the way for a promising approach to enhancing diagnostic capabilities. The integration of computer-aided diagnosis (CAD) systems emerges as a major advancement in the realm of skin cancer diagnosis, offering the potential for faster and more accurate assessments. However, the fight against skin cancer remains an ongoing journey, demanding continuous research and innovation to refine these AI-based methodologies and forge a symbiotic relationship between technology and medical expertise. By harnessing this synergy, the potential emerges not only to improve diagnostic accuracy but also to potentially reshape the landscape of skin cancer management, thereby contributing to the enhancement of patient well-being.

Abbreviations

ML	Machine Learning
DL	Deep Learning
CAD	Computer-Aided Diagnosis
CNN	Convolutional Neural Network
AI	Artificial Intelligence
BCC	Basal Cell Carcinoma
SCC	Squamous Cell Carcinoma
MCC	Merkel Cell Carcinoma
KS	Kaposi Sarcoma
DFSP	Dermatofibrosarcoma Protuberans
SVM	Support Vector Machines
CBR	Case-Based Reasoning
GANs	Generative Adversarial Networks
RBF	Radial Basis Function

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