AN OVERVIEW ON SKIN CANCER DETCTION APPLYTING DEEP LEARNING TECHNIQUES FROM DERMOSCOPIC SKIN LESION IMAGES

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Abstract. Skin cancer is the most prevalent type of cancer in the world that can be an abnormal growth, an unhealed wound, or an alteration in a mole for which detection of skin cancer becomes confusing in some cases. Almost all of the skin cancers are treatable and do not cause any death unless it spreads to or around the lymphatic nodes or any other organs. Early identification of skin cancer is necessary to ensure proper treatment in time to protect the patient's precious life. Early detection of skin cancer can be significantly aided by automated methods. In recent times, deep learning models are employed for medical image processing and disease diagnosis. Among the deep learning models, the Convolutional Neural Network has drawn a significant amount of interest because of its great performance and adaptability. Besides CNN, GAN and machine learning techniques associated with deep learning models have left notable efficiency in detecting and classifying various categories of skin cancer. In the paper, a comprehensive analysis has been drawn answering research questions reviewing recent prominent journals related to detection and classification of skin cancer from dermoscopic skin lesion images.

Keywords: Dermoscopic skin cancer lesion image, Melanoma, Basal Cell Carcinoma, Deep learning models, Convolutional Neural Network, Generative Adversarial Network.

1. Introduction

Skin cancer develops when skin cells increase and spread in an unchecked, disorderly manner [1]. Skin changes are the most typical indication of skin cancer. It has various appearances. This can be an abnormal growth, an unhealed wound, or an alteration in a mole [2]. The majority of skin cancers develop in elderly persons on sun-exposed body parts or in those with compromised immune systems. Persistent dermal contact with substances like coal and tar is another factor in the progression of skin cancer [3]. The world's highest incidences of skin cancer are found in Australia every year, where rates are between two and three times higher than in the UK, the USA and Canada. Approximately 80% among all cancers that are diagnosed each year in Australia are skin cancers [4]. Skin cancer also ranks as the most prominent type of cancer among Americans. It affects 20% of Americans at some point in their lives. Every day, 9,500 of American people receive a skin cancer diagnosis [5]. Approximately 80% among all cancers that are diagnosed each year in Australia are skin cancers [4]. The most widespread kind of cancer affect Americans is also skin cancer. Skin cancer affects 20% of Americans at some point in their lives. Every day, 9,500 of American people receive a skin cancer diagnosis [5] [6]. Seborrheic keratosis and skin vascular tumors, on the other hand, are the benign varieties of skin cancer because they carry a potential risk of developing skin cancer in the future. Melanocytes are the cells that produce melanin where melanoma skin cancer develops [3]. The most prevalent and typical type of skin cancer that appears in the basal cell layer of the skin is basal cell carcinoma [7]. Cells that produce lymphatic or blood vessels give rise to skin vascular tumors. They could develop within the skin or beneath it. Hemangioma is the most prevalent variety of skin vascular tumor. Most skin cancers are treatable if they are found early and given

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the appropriate treatment. [4]. For these reasons, early skin cancer detection is essential for preserving human lives. In this situation, automated skin cancer detection can be useful. Deep learning models have been used for disease diagnosis and medical image processing throughout the past few years. Among the various deep learning architectures, Convolutional Neural Networks have generated the most interest due to their better performance and adaptability. In addition to CNN, GAN and machine learning methods linked to deep learning models have demonstrated noteworthy effectiveness in identifying and categorizing different types of skin cancer.

On this subject, a substantial amount of study has been done. As a result, it's critical to compile, evaluate, categorize, and synthesize the existing research findings. We developed search strings to assemble pertinent data in order to conduct a comprehensive systematic assessment of skin cancer detection methods utilizing deep neural network-based categorization. We restricted our search to materials from reputable journals and conferences. The articles were carefully analyzed and evaluated from many angles. Current developments in skin cancer detection techniques give us tremendous hope, but there is still room for advancement in the diagnostic methods we currently practice.

The remainder of the section flows as follows, the study methodology for carrying out the efficient examination of deep learning algorithms for skin cancer diagnosis is described in Section 2. It includes information about the review field, search terms, search criteria, information sources, and selection standards. Section 3 provides a thorough examination of detection methods. Section 4 describes the dataset utilized in the research investigations and Section 5 provides the challenges in skin cancer detection applying deep learning techniques and relevant solutions. Contribution of the study is described in Section 6, and the study's conclusion is presented in Section 7.

2. Review Approach

The goal of this comprehensive literature is to identify and classify the most effective methods for employing deep learning methods to recognize skin cancer. Systematic reviews of the literature compile and evaluate previously published studies using predetermined assessment criteria. Such reviews aid in establishing what is currently known in the relevant field of research. Deep neural network-based publications on the diagnosis of skin cancer made up the majority of the studies taken into account in the comprehensive literature analysis.

2.1 Questionnaire for Research

For establishing an organizational framework for the research studies related to skin cancer by means of deep learning techniques, following are some of the questions that have been compiled.

Table 1. Question for research for organizing the research studies related to skin cancer.

Question No	Question Details
Q1	What are most significantly efficient deep learning approaches to diagnose and categorize skin cancer?
Q2	What are the available various datasets for classifying distinctive skin cancer types?

2.2 Source of Information

An organized evaluation is necessary for a full analysis of the material being reviewed. Therefore, before the search began, the right selection of databases was made in order to enhance the chances of discovering highly relevant publications. The review included an internet database search for the following ones:

- Google Scholar
- ACM
- IEEE Xplore
- Springer
- MDPI
- Science Direct
- ArXiv

2.3 Basis on the Inclusion

The research articles incorporated into the review considered a number of factors, which served as the basis for inclusion. In addition to the papers that have been retrieved via a few inquiry strings, there is a supplementary table regarding the query and taken criteria.

Table 2. Inclusion criteria for conducting query

Inclusion Criterion
Papers from the years 2018 to 2022 are covered.
Convolutional neural networks or CNN, generative adversarial networks or GAN, deep learning, and skin cancer classification-related publications that match the titles have been considered.
Already cited papers are included
Papers published in English language are considered

The present paper was generated after an in-depth review of the databases to guarantee the accuracy of the study. But for a variety of factors, several notable publications have been skipped because they do not correspond to the title and concept significantly related to the subject of skin cancer identification or classification. Therefore, an exhaustive and comprehensive review of all the current research was done towards achieving the objective. Certain query strings are “skin cancer”, “skin cancer classification”, “detection of skin cancer”, “skin cancer diagnosis”, “skin cancer classification using deep learning methods” and “skin cancer classification using Convolutional Neural Networks”.

3. Deep Learning Techniques for the Detection of Skin Cancer

Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and combinations of CNNs with machine learning techniques are examples of deep learning approaches that have demonstrated significant promise for the early diagnosis of skin cancer. This section evaluates the research question Q1. An outline of these strategies is provided below:

Convolutional Neural Networks (CNNs)

The capacity of CNNs to automatically learn discriminative characteristics from photos has made them a popular choice for skin cancer screening. Convolutional, pooling, and fully connected layers are all part of

CNN architectures, which have several layers altogether. In order to accurately classify skin lesion photos, these networks can learn hierarchical representations of the data.

Generative Adversarial Networks (GAN)

A discriminator network and a generator network are the two neural networks that make up a GAN. GANs have the ability to produce images of fabricated skin lesions that closely resemble actual lesions. This is accomplished by an adversarial method of training where the generator attempts to deceive the discriminator through the creation of realistic images, whereas the discriminator seeks to discern between genuine and synthetic images. Adding more training samples and increasing the dataset's variety are all possible uses for GANs for data augmentation.

Combining CNNs with Conventional Machine Learning Methods

Deep learning models and conventional machine learning methods can be coupled to enhance the detection of skin cancer. A machine learning method, such as Support Vector Machines (SVMs) or Random Forests, can be used to classify photos of skin lesions using CNN characteristics, for instance. This combination of machine learning and deep learning methods can make use of the advantages of both methodologies and possibly enhance detection performance.

It should be noted that these methods need broad and varied datasets of skin lesion images for training. To increase the robustness and generalizability of the models, appropriate preprocessing methods, such as image normalization and augmentation, are crucial. Furthermore, optimal techniques for model training and evaluation should be used, including cross-validation and performance indicators like accuracy, sensitivity, specificity, and area under the curve (AUC). In general, deep learning methods, such as CNNs, GANs, and combinations with machine learning, offer potential ways to identify skin lesions accurately and automatically, which could lead to the early identification of skin cancer. The effectiveness and precision of skin cancer diagnosis could be increased by dermatologists using these methods.

3.1 CNN Related to Skin Cancer Detection

Table 3 evaluates and exhibits recent research study concerning CNN approaches for diagnosis of skin cancer.

Table 3. Question for research for organizing the research studies related to skin cancer.

Ref	Details	ML Technique	Identification and Classification	Dataset	Results	Limitations
[8]	Utilized deep transfer learning to categorize images of skin lesions into seven groups.	Deep learning and CNNs	Seven Category;Melanoma, Basal Cell Carcinoma, BKL, Vascular Lesion/Melanocytic Nevi, Actinic Keratosis,AKIEC,Dermatofibroma	HAM 10000	82.9% Accuracy	Dataset inequalities, a shortage of images within certain categories and huge number of classes.
[9]	Employed VGG19 Model to classify three distinctive kinds of skin cancer.	VGG-19	Three Category; Non-cancerous benign keratosis lesion and cancerous type basal cell carcinoma and dermatofibroma	HAM 10000	98.5% Accuracy	The used dataset is not labeled and the input size is 64 by 64 which is quite small
[10]	Implemented CNN with other pretrained models InceptionV3, ResNet50, Inception- ResNet.	CNN, InceptionV 3,ResNet50, Inception-ResNet	Two Category; Non- melanocytic and melanocytic skin lesions	ISIC 2018	85.8%(v3) 83.7%(ResNet50); 84%(InsepResNet)	A large group of datasets is required to train and test the network.

[11]	Implemented CNN based MobileNetV1 and DenseNet121. Unet is applied for separating skin cancer portion.	MobileNet V1, DenseNet1 21	Two Category: Melanoma, non-melanoma	ISBI 2016	96%(Mob ileNe tV1) 95.8% (DenseNe t 121)	Limited data, challenges in thoroughly examining the discriminative ability of lightweight deep learning network
[12]	Suggested model better performed. Inception-V3, Inception ResNetV2, DenseNet169, MobileNet	ResNet50	Two Category : Melanoma, non-melanoma	ISIC	93.5% Accuracy	Binary classification is performed.
[13]	A GPU is developed lesion pattern analysis. Image illumination had an impact on the way the system functioned.	CNN	Two Category: Benign and malignant skin Lesion (melanoma)	ISIC, MED-NODE	77.5% Accuracy	Accuracy of the system is low comparing other model's performance and binary categorization is done.

3.2 GAN Related to Skin Cancer Detection

The Table 4 in the below analyzes and illustrates recent research studies concerning GAN approaches for skin cancer diagnosis.

Table 4. Existing research analysis based on GAN Related to Skin Cancer Detection

Ref	Details	ML Technique	Identification and Classification	Dataset	Results	Limitations
[14]	Employed GAN with Attention mechanism SPGGAN.	GAN with SPGGAN	Seven Category; basal cell carcinoma, vascular lesion, melanoma, actinic keratosis, melanocytic nevus, dermatofibroma and vascular lesion	HAM 10000	70.1% Accuracy	The dataset is not labeled.
[15]	CNN is used as discriminator and generator in GAN	GAN	Seven Category; melanoma, vascular lesion, basal cell carcinoma, benign keratosis, actinic keratosis, dermatofibroma and melanocytic nevus	ISIC 2018	86.1% Accuracy	It is quite likely that if trained from beginning, deep learning models will perform better than the GAN.
[16]	Employed data augmentation technique with GAN	GAN	Three Category; seborrheic keratosis, nevus and melanoma	PH2, ISIC 2018, ISIC 2017	91.5% AUC	A large group of datasets is required to train and test the network

3.3 Deep Learning with Machine Learning Techniques Related to Skin Cancer Detection

The subsequent Table 5 analyzes and presents recent research studies concerning deep learning using machine learning approaches for skin cancer diagnosis.

Table 5. Existing research analysis based on CNN with Machine Learning Techniques Related to Skin Cancer Detection

Ref	Details	ML Technique	Identification and Classification	Dataset	Results	Limitations
[17]	Implemented SVM and KNN for classification besides CNN	CNN, SVM and KNN	Two Category; Benign and malignant skin lesion	ISIC	85%, 90% Accuracy	Determining between benign and malignant skin lesions only.
[18]	Utilized ANN, PSO and KNN for classification.	ANN, PSO, KNN	3 Category: squamous cell cancer, melanoma and basal cell carcinoma	Unknown	98.75%	Utilized dataset is unknown.
[19]	Applied KNN for feature extraction and categorization	KNN	Two Category: Non-melanoma and melanoma	PH2	92.7% Accuracy, 84.44% specificity	The only categorization done is binary.
[20]	SVM, KNN, and Random Forest are used for categorization after the Watershed segmentation approach is employed.	SVM, KNN, Random Forest	Two Category: Melanoma and non-melanoma	ISIC	89.43% (SVM), 69.54% (KNN),76.87% (Random Forest)	Only melanoma detection is performed. Only machine learning method cannot provide higher accuracy.
[21]	Applied ResNet152, InceptionV4, DenseNet-161 for categorization and utilized VGG16 in training Unet	VGG16, ResNet152, InceptionV4, DenseNet-161	Three Category: seborrheic keratosis, squamous cell carcinoma and melanoma	ISBI 2017, MED-NODE	90% Precision (ResNet152)	The model will be able to learn feature with higher batch size.Coupling this parameter by linking a stochastic function will enhance the accuracy.
[22]	Proposed CNN architecture with SVM and KNN	CNN, SVM , KNN	Two Category: benign and malignant melanoma	ISIC	85.5% Accuracy	Only melanoma detection is performed.

The Table 3, 4, and 5 show a comparison of the machine learning methods utilized, classification categories for skin cancer, datasets, outcomes, and limitations for CNN, GAN, and CNN with deep learning methods according to research papers.

4. Available Datasets for Skin Cancer Detection

This section evaluates the research question Q2. For the aim of development and research, there are numerous freely accessible datasets for skin cancer assessment. Some of the notable datasets for identifying and classifying skin cancer are in the following.

ISIC (International Skin Imaging Collaboration) Repository: There is a sizable collection of skin photos in the ISIC library, covering both benign and malignant skin lesions. It is among the datasets that are most frequently used to find skin cancer [23]. ISIC 2016 is the first available dataset. There are several versions of the ISIC 2016 dataset as well, including ISIC 2017, ISIC 2018, and ISIC 2019.

HAM10000: 10,015 dermoscopic images of skin lesions including various forms of skin cancer are included in the HAM10000 dataset [24].

PH2: Dermoscopic images of benign and malignant pigmented skin lesions make up the PH2 collection. There are 200 photos in all, each with accompanying ground truth annotations [25].

Dermnet: Images of 23 different types of diseases of the skin constitute the data. There are around 19,500 images total, of which 15,500 have been divided between the training and test set. [26]

Dermofit Image Library: 1,300 clinical and dermoscopic photographs of skin lesions, including both benign and malignant instances, are available in the Dermofit Image Library. It can be accessed for free to conduct research [27].

Melanoma SIIM-ISIC Classification: This dataset, which includes over 33,000 dermoscopic images of skin lesions, including melanoma and benign lesions, was made available for the ISIC 2020 competition [28].

MED-NODE: The dataset comprises of 100 and 70 images of naevus and melanoma respectively taken from the Department of Dermatology's digital image library at the University Medical Center Groningen (UMCG). These images were used to test and refine the MED-NODE system for skin cancer identification from macroscopic images [29].

Table 6. Datasets used in the research studies for diagnosis of skin cancer

Dataset	Ref.
HAM10000	[8], [9], [14]
PH2	[16], [19]
ISIC	[12], [13], [17], [20], [22]
ISIC 2017	[16]
ISIC 2018	[10],[15],[16]
ISBI 2016	[11]
ISBI 2017	[21]
MED-NODE	[13],[21]

The datasets utilized in the research investigations are shown in Table 6, where we observe that the ISIC serves as dataset for identification of skin cancer most frequently.

5. Challenges in Skin Cancer Detection Using Deep Learning Techniques and Relevant Solutions

Early identification is essential to enhancing patient outcomes in the treatment of skin cancer, which is a significant public health concern. The automated identification of skin cancer from medical images has showed potential thanks to deep learning algorithms. However, in order to improve the precision and dependability of these models, a number of issues must be resolved. In this paper, we outline the main issues and suggest workable solutions in the area of deep learning models for skin cancer diagnosis.

Limited and Unbalanced Data:
Deep learning models need vast and diversified datasets for efficient training, which is a challenge. It can be difficult, though, to compile a large collection with enough photos of skin cancer. Additionally, biased model performance might result from unbalanced class distributions, where some forms of cancer of the skin are underrepresented. Increasing the sample size and strengthening model generalization can be accomplished by augmenting the present data set using strategies like rotation, scaling, and flipping. The pretrained methods, including those trained on natural picture datasets as ImageNet, can be fine-tuned on data related to skin cancer in order to take use of their learned characteristics and lessen the requirement for prolonged training on sparse data. Promoting data exchange and cooperation between research organizations can aid in the development of larger, more varied datasets that better reflect the variety of cases of skin cancer.

Explicitness and Interpretability:
Machine learning models frequently lack comprehension, making it challenging to comprehend the underlying variables influencing their conclusions. Interpretability is essential for fostering clinical acceptance and fostering trust in medical procedures like skin cancer diagnosis. By including mechanisms for attention within deep learning techniques, it is possible to draw attention to key areas of an image and gain understanding of how the algorithm makes decisions. Techniques for Explainable AI (XAI) Saliency maps, gradient- based approaches, or rule-based approaches are XAI techniques that can be used to produce explanations behind predictions made by models, allowing physicians to comprehend and validate the justifications for the decisions.

Generalization and Robustness:
Deep learning algorithms may struggle to generalize effectively to new data or display vulnerability to hostile attacks, producing predictions that are incorrect or unreliable. Regularization techniques, such as batch normalization, dropout, and L1/L2 regularization, can be used to reduce overfitting and enhance model generalization. By utilizing a variety of predictions, combining numerous models of deep learning, through either model averaging or enhancing, can improve overall performance and resilience. Using adversarial training methods can make models more resistant to attacks and ensure their robustness against input picture manipulation.

Integration and Validation in Medical Practice:
Deep learning models need to be rigorously validated and incorporated into current healthcare workflows in order to move from study to clinical practice. Clinical standards should be used to compare the performance of models, and deployment issues like hardware needs and compliance with regulations must be resolved. Working with experts and medical professionals can make it easier to validate a model's performance against the needs of actual clinical settings. To guarantee consistent and accurate performance assessment, standard evaluation techniques and standards for models using deep learning in the detection of skin cancer should be

established. Following rules, such as those governing privacy and data security, can assist in overcoming deployment difficulties and guarantee that you meet healthcare standards.

Deep learning methods have enormous promise for detecting skin cancer. We can enhance the efficacy, dependability, and acceptance of these models by addressing issues with data accessibility, comprehension, generalization, and clinical integration.

6. Contribution to the Study

In contrast with the challenges and limitations including limited and unbalanced data, generalization and robustness of the model, explicitness and interpretability and binary classification of skin cancer of the recent existing research study, to sort of overcome these challenges, three pretrained architectures VGG-19, NasNet-Large and DenseNet-201 are utilized. A combination of the Dermnet and ISIC datasets consisting of 2072 dermoscopic skin cancer lesion images are utilized for classifying the skin cancer types into four different including basal cell carcinoma, seborrheic keratosis, melanoma and skin vascular tumors. To address the data insufficient concern and enhance the efficacy of the model, augmentation techniques such as brightness, rescaling, shear ranging, horizontal flip, rotating and zooming are applied. The accuracy of the classification models VGG-19, NasNet-Large and DenseNet-201 are 87%, 77.78% and 73.61% respectively. Since the pretrained VGG-19 model performs better, this model is considered as the proposed model for classification. Furthermore, to highlight and localize the lesion in the dermoscopic image of skin cancer, the gradient centered Grad-CAM method is used. The pretrained Xception model is applied to implement the Grad-CAM model.

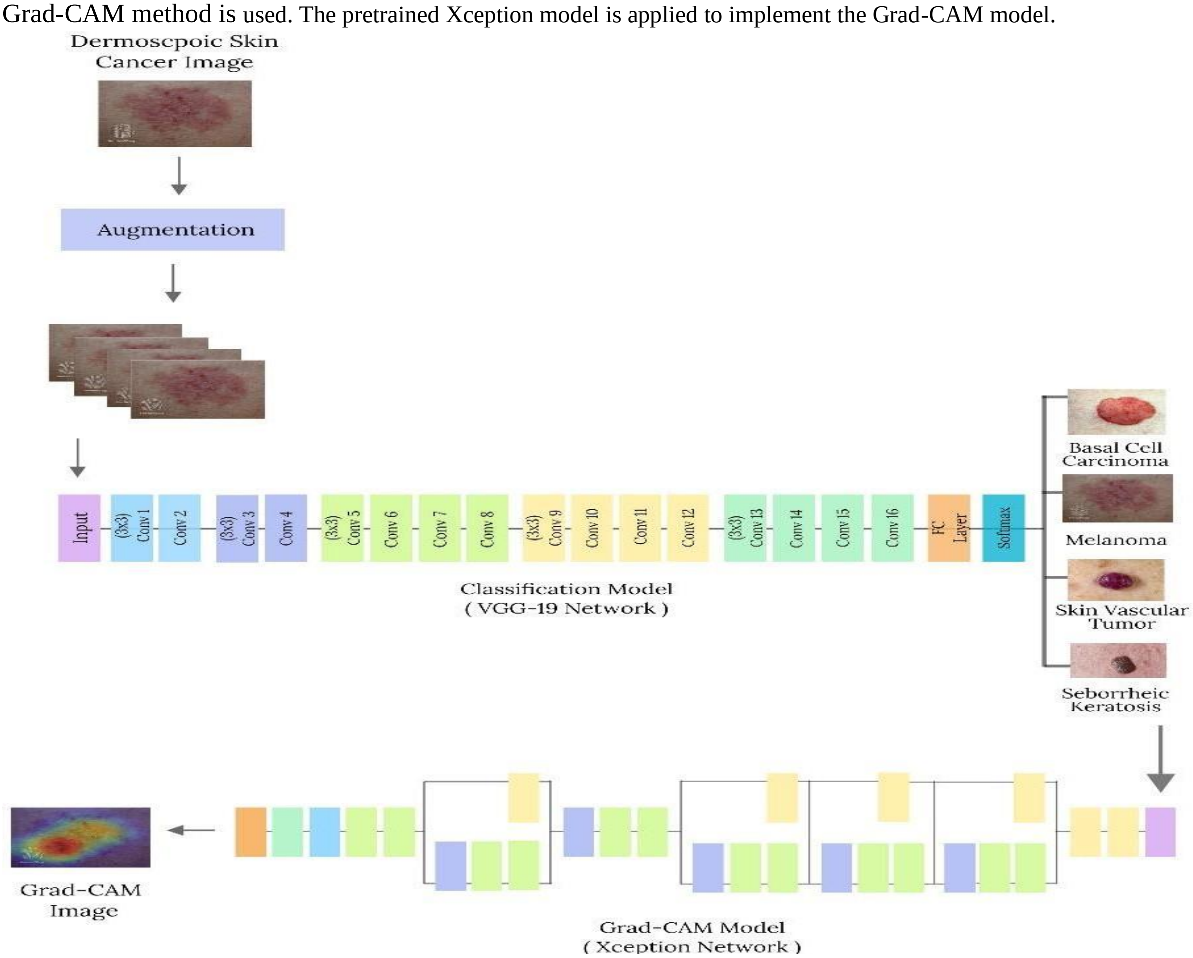

Fig. 1. Architecture of the proposed system for identification of skin cancer

The model generates the heatmap and Grad-CAM images corresponding to each category of images depicting and highlighting the region containing the features of different skin cancer categories. The proposed model architecture is illustrated in fig. 1.

Though the performance of the proposed classification model VGG-19 is relatively low than other existing classification tasks of skin cancer, addition to classification the proposed model is able to emphasize and localize the skin lesion that have features of skin cancer using the Grad-CAM model.

7. Conclusion

The usage of Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), and the fusion of CNN with machine learning methods for skin cancer diagnosis were examined in this research. When it comes to automating the detecting process and increasing diagnostic accuracy, these sophisticated deep learning models have demonstrated encouraging outcomes. Researchers have discovered a way to extract high-level information from images of skin lesions using CNN architectures. The sensitivity and specificity of CNNs have shown to be greater, making them effective instruments for the early identification of skin cancer. The abilities of detection of skin cancer systems have been considerably improved by the inclusion of GANs. The creation of realistic and varied generated skin lesion images made possible by GANs can be used to supplement small datasets. By addressing the issue of small and unbalanced datasets, this data augmentation strategy has enhanced the generalization of models and performance. Furthermore, a hybrid methodology for skin cancer diagnosis has been developed by fusing CNN with conventional machine learning methods. Researchers have improved the models' interpretability, precision in classification, and robustness by using machine learning algorithms like Support Vector Machines (SVM) or Random Forests. The use of machine learning approaches improves the general efficacy of the skin cancer detection technique by enabling efficient selection of features, model optimization, and ensemble learning. However, the field still faces a number of obstacles. The availability of data, especially large and varied datasets, remains to be a barrier. Additionally, for deep learning models to be trusted and accepted in therapeutic contexts, interpretability are essential. The clarity and interpretability of the algorithms can be improved by additional study on understandable AI methods and attention mechanisms. Thorough validation against clinical requirements and adherence to regulatory directives are crucial for successful clinical integration. Deep learning models may be seamlessly integrated into current healthcare workflows thanks to the collaborative efforts of researchers and medical experts.

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