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Deep Learning for the Detection of Skin Cancer: A Comprehensive Review

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***Abstract*— Since skin cancer is a common and sometimes fatal illness, prompt diagnosis is essential to providing the best possible care. At times the application of learning methods has been demonstrated to be highly beneficial, in the fields of medical image analysis particularly, in the detection of skin cancer. In this review, we aim to provide an overview of how deep learning methods are utilized in the diagnosis of skin cancer. We will summarize the methods, challenges and advancements, in this field. After that it proceeds to elaborate on the concepts of learning and why it is suitable, for assessing dermatological image analysis. In the paper various architectures of networks are examined, demonstrating their remarkable effectiveness, in tasks such, as segmenting lesions classifying them and determining their location. These consist of networks (CNNs) recurrent neural networks (RNNs) and variations. The research paper also explores the significance of datasets, in developing and evaluating algorithms and their crucial role in training deep-learning models, for skin tumor diagnosis. It delves into the importance of utilizing domain adaptation techniques transfer learning and data augmentation methods to increase the performance and resilience of models. The paper also talks about the concept of interpretability. Explores the challenges of using learning models, in dermatology. It emphasizes the importance of having comprehensible methods, in settings. Combining the power of learning with the field of dermatology presents prospects, for improving the timely identification, prediction of outcomes and overall well-being of patients undergoing treatment, for skin cancer.**

***Keywords*— Skin Cancer, Deep Learning Models, CNNs, RNNs, Detection.**

I. INTRODUCTION

Skin cancer begins when skin cells proliferate. Skin cancer affects many people and has major public health repercussions. Skin cancer is frequent worldwide and is rising. UV light from sunlamps and tanning beds can cause skin cell proliferation and growth. Skin, sunburns, family history of skin cancer, and unique moles all raise the risk of skin tumors [1] [2]. Based on estimates, from both the International Labor Organization (ILO) as well as the World Health Organization (WHO) around one out of every 3 deaths caused by melanoma skin tumor is linked to exposure, to the sun. The incidence of skin tumor that is not melanoma is increasing among individuals who work outdoors as indicated by a study published in Environment International. To mitigate the occurrence of worker fatalities, in this work environment proactive measures need to be implemented. Skin cancer has been increasing over the years impacting individuals, across age groups and ethnicities [2]. Skin cancer is more common in regions with high sunlight exposure, such as Australia and New Zealand, where UV radiation significantly increases its prevalence. It poses serious health risks, financial burdens, and strain on healthcare systems. The three main types are melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). While non-melanoma cancers like BCC and SCC are less fatal, untreated cases can lead to complications. Melanoma, although less common, is more aggressive and likely to spread [3]. Prevention efforts focus on sun protection through clothing, sunscreen, and limiting sun exposure. Early detection via skin checks and screening programs is crucial to reducing healthcare impacts. Traditionally, dermatologists relied on visual inspections and biopsies for diagnosis, which can be time-intensive and subjective [4] [5]. Skin cancer is an occurring health concern that can be avoided and has effects, on both individuals and society. Efforts to promote health by focusing on detection, education and prevention play a crucial role, in reducing the occurrence and impact of skin cancer [8] [10]. Advances in deep learning (DL) have revolutionized skin cancer detection by automating and enhancing diagnostic accuracy [6] [7]. These methods, including neural networks like CNNs, address the limitations of traditional approaches and offer scalable solutions [9]. This review highlights the strengths and challenges of DL in detecting skin cancers, ethical concerns, and its potential impact on prognosis, early intervention, and patient care. Continued research aims to refine DL algorithms, ensuring their effectiveness in clinical practice.

II. RELATED WORK

Deep learning algorithms for skin tumor detecting are covered in recently reported articles in the relevant works.

Gajera et al. [26] proposed a pre-trained CNN-based automatic melanoma classification technique in Fig. 1. Along with the eight most popular CNN models, AlexNet, VGG-16, VGG-19, Inception v-3, ResNet 50, MobileNet, EfficientNet B0, and DenseNet 121 were used on four skin tumor datasets: ISIC 2016, ISIC 2017, PH2, and HAM10000. The feature extractor was DenseNet and the classifier was MLP, which had the highest categorization accuracy at 98.33% and an F1 score of 0.96. PH2, ISIC 2016, and ISIC 2017 training images of 200, 900, and 2000 were used to evaluate the suggested strategies. Deep architectures using small datasets like DenseNet-121 may overfit. HAM10000 dataset categorization was low.

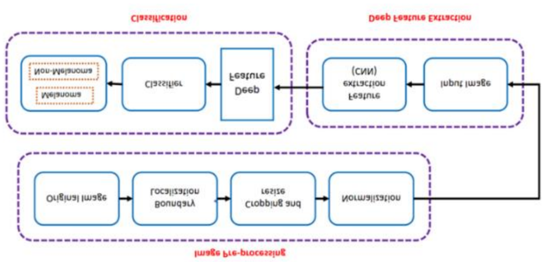

Fig 1. Proposed in [26] is an automated classification network.

Alenezi et al. [27] suggested categorizing skin cancer using a pre-trained deep residual network trained on the HAM1000 and ISIC 2017 datasets Fig. 2 . They removed hairs from skin lesion images using wavelet transform and pooling. ReLU, PReLU, Sigmoid, and Hardlim were tested to find the activation function with the maximum classification accuracy on skin lesion datasets. The ReLU activation function has the highest categorization accuracy (96.91%) and F1-score (0.95).

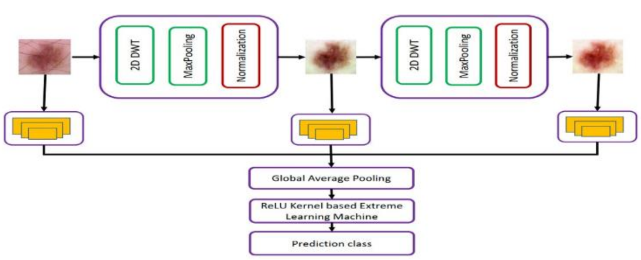

Fig 2. A network for automated classification was proposed in [27].

Shinde et al. [28] used MobileNet with the squeeze method in Fig. 3 to improve skin lesion categorization. Squeezing skin lesion photos increased accuracy and reduced dataset size for the Raspberry Pi 4 board. The suggested Squeeze-MNet technique outperformed Inception V3, MobileNetV2, and VGG-16 on the ISIC dataset with 99.36% accuracy. This study's model had lower sensitivity and specificity than baseline models. This model was designed for Internet of Things categorization, hence it should have less training parameters than MobileNetV2. There were additional parameters and training time than MobileNetV2.

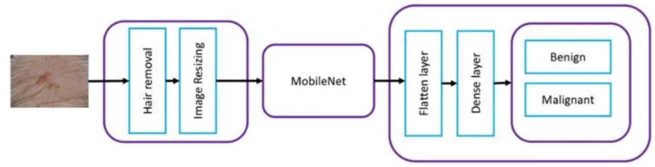

Fig 3. The architecture that was suggested in [28].

Alenezi et al. [29] used dilation, normalization, and pooling to eliminate hairs from skin lesion images. They trained the SVM classifier to classify melanoma using alleviated feature selection to choose ResNet-101 features. Also, trained SVM utilizing ResNet-101, AlexNet, DarkNet 19, GoogleNet, SqueezeNet, Xception, and MobileNetV2 features. Using features extracted using these methodologies, SVM achieved 96.15% and 97.15% accuracy on ISIC 2019 and 2020. Only 1168 pictures comprised Dataset 1. Deep architectures like ResNet-101 were used for feature extraction, which may overfit because of its small dataset. Limitations of the suggested study include SVM classifier parameter selection time. Bechelli & Delhommelle [30] compared deep learning and machine learning algorithms for skin tumor categorization tested pre-trained deep learning models VGG16, Xception, and ResNet50 on the HAM10000 and ISIC datasets, as well as machine learning algorithms, logistic regression, linear discriminant analyses, k-nearest neighbor's classifier, decision tree classifier, Gaussian naive Bayes, and CNN. Deep learning models outperformed machine learning in skin cancer classification; VGG-16 had the highest accuracy of 88% and an F1-score of 0.88. The deep learning models' accuracy and F1 on the HAM10000 dataset were worse than on the ISIC dataset, which had fewer images. The best architecture, VGG-16, had 0.70 accuracy and 0.68 precision. The findings suggest that not all datasets are suitable for deep model training.

The integration of deep learning algorithms into portable hand-held devices such as smart phones and dermoscopy holds great promising for dermatological practice, especially in the area of skin cancer diagnosis. These devices provide timely, convenient and inexpensive diagnostic tests in academic affiliate and telemedicine practice. The advantages include enhanced interactiveness and accessibility, near real-time analysis, and simplicity in employment for those with little computational knowledge. But there are issues such as hardware constraints, improving model accuracy, data protection which are worth solving. For these implementations to be possible, improvements to the effective and efficient neural structures, edge AI, and hardware add-ons are required to operate within the local computing constraints of portable devices.

Mazoure et al. developed DUNEScan, a web-based skin lesion photo classification system [31]. Trained six deep learning networks—Inceptionv313, ResNet5014, MobileNetv23, EfcientNet15, BYOL16, and SwAV—to predict skin malignancies on the ISIC archive. Compare the web server's average model prediction to the binary dropout approximate posterior. ResNet-50 gave melanoma a maximum class prediction probability of 1.00. Though it only distinguished benign and malignant instances, the web server had a flawless class forecast probability of 1.00. Check it on multiple datasets. Ghosh et al. classified skin cancer using AI [6]. It was advised to categorize skin images using CNN-based SkinNet-16 trained on ISIC and HAM10000. PCA shrank the data. After exploring numerous interbreeds, the Adamax optimizer had a maximum validation accuracy of 95.51% on the HAM10000 and 99.19% on the ISIC dataset. The suggested approach will be tested on multi-class categorization difficulties and huge datasets as it was only tested on binary categorization. Fraiwan and Faouri presented AI-based skin tumor classification [19]. They separated skin cancers from HAM1000 images using thirteen pre-trained deep convolutional neural network models. DenseNet201 obtained the highest accuracy (82.9%, F1-score 0.744). Because HAM10000 is unequal, F1-score is superior for performance analysis. This study has a dismal 0.7424 F1-score. Our goal is to properly and dependably forecast skin cancer photos, thus the offered approach may not diagnose skin cancer. This study found limited recall and precision using the suggested strategy.

A novel neural network with modified and convolutional capsule layers was proposed by Goceri. Goceri [32] presents a capsule-layered network. It is shown how successfully the suggested network categorizes skin tumors into multiple classes. Comparisons of capsule networks for skin tumor classification are available. Test findings reveal the suggested network classifies seven skin cancers with 95.24% accuracy.

III. Skin Cancer Types

Abnormal growth and development of skin cells are indicators of skin tumor. This part offers a summary of the most prevalent kinds of skin tumor.

1) Basal cell carcinoma (BCC): The most common type of skin malignancy. Usually, fair-skinned people acquire BCC. Dark-skinned persons get skin cancer more easily. BCCs look like pink patches, pearl-shaped lumps, or flesh-coloured spheres. BCCs grow after years of sun exposure or indoor tanning. BCCs usually occur on the head, neck, and arms, although they can also form on the belly, legs, and chest. Early detection and treatment of BCC are crucial. BCC can spread. Damage and deformity can result from bone and nerve penetration [11].
2) Squamous cell carcinoma (SCC) is the most common type of skin tumor. Lighter skin tones are more vulnerable to SCC, but darker skin can also develop it. SCC symptoms include a scaly patch, red, hard lump, or reopening sore. Sun-exposed skin on the ear rim, face, neck, arms, chest, and back is more susceptible to develop SCC. Deep skin penetration by SCC can cause damage and disfigurement. Early detection and treatment can stop SCC from spreading. Precancerous skin development can cause SCC [13].
3) Melanoma: Known as "the most serious skin cancer" due to its rapid spread. Melanoma can occur anywhere on your body, in healthy skin or in a cancerous mole. Melanoma generally affects men's faces or trunks. Men and women without sun exposure can acquire melanoma. Early melanoma diagnosis and treatment are crucial [14].
4) Skin Lymphoma: A non-Hodgkin lymphoma that primarily affects the skin, also known as cutaneous lymphoma. The lymphatic system, part of the immune system, grows lymphomas. Symptoms of skin lymphomas vary by type and stage, but they often include lumps, itchy skin, rash, red patches, and lesions that look like other skin disorders. The type and amount of lymphoma must be determined by a skin biopsy and possibly other tests. Topicals, systemic medicines, phototherapy, radiation therapy, and stem cell transplantation can treat skin lymphomas. The treatment for cutaneous lymphoma depends on its type, stage, and patient characteristics [15].
5) Merkel Cell Carcinoma (MCC): A rare but serious skin cancer. It develops in epidermal Merkel cells, which are essential for touch perception. Merkel cell carcinoma can grow in non-sunny skin, however, it usually appears on the face, neck, and arms. Merkel Cell Carcinoma usually appears as a painless, firm, flesh-coloured or bluish-red lump on the skin. It can rapidly spread to nearby lymph nodes or organs such as the liver, brain, lungs, or bones. Radiation, surgery, chemotherapy, and immunotherapy are used to treat Merkel cell cancer. Merkel cell cancer outcomes improve with early discovery and therapy [16].
6) Actinic Keratosis: This precancerous skin condition, also known as solar keratosis, is caused by chronic sun exposure or UV radiation, primarily from sunlight. These lesions appear as tiny, crusty lumps or rough, scaly patches on sun-exposed skin like the face, ears, scalp, neck, backs of the hands, and forearms. Even while actinic keratosis is not a skin cancer, a small fraction of these lesions can develop into squamous cell carcinoma if left untreated [17].
7) Dysplastic nevi: These mottling abnormalities, also known as atypical moles, may differ from normal moles (common nevi). Dysplastic nevi may increase the risk of melanoma, a severe skin cancer. Fig. 4 shows skin cancer images [18].

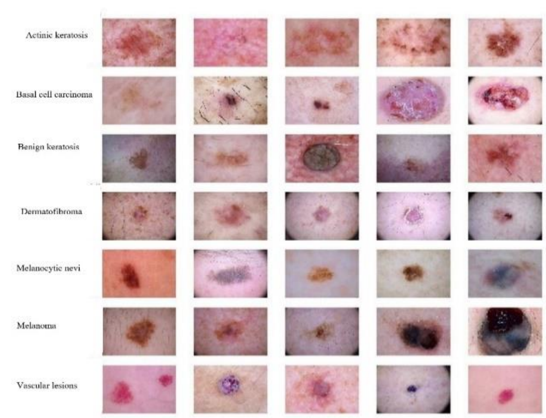

Fig 4. Some of skin cancer images in [25]

IV. Deep learning models

They will summarize skin tumor diagnosis learning methods in this part. Deep learning architectures utilized in this sector include:

1) CNNs: Convolutional neural networks (CNNs) analyze visual data like images and videos. CNNs are built for grid-like input. Object detection, image categorization, and image identification are their strengths. CNNs are inspired by how animal visual cortex neurons are organized in response to visual field areas. Image-based tasks like skin lesion categorization are commonly used with CNNs. Their outstanding efficacy in learning hierarchical features from photographs makes skin lesion photos easier to analyze [20][12].

2) Residual Networks (ResNets): A type of deep neural network design. To solve the fading gradients problem in extremely deep neural networks, ResNets included skip connections or shortcuts. Their effective deeper model training has led to skin cancer diagnosis [21].

3) Inception Networks (GoogleNet): Google researchers developed Inception Networks, or GoogleNet, a deep convolutional neural network topology for precise and efficient picture categorization. These networks efficiently collect features at several scales using modules with different filter sizes. Skin lesion categorization uses inception networks to increase feature extraction [22].

4) DenseNet: Creates densely linked architecture between layers in a block, unlike traditional CNNs. This thick link is achieved by concatenating the feature maps of the previous layers and inserting them into the next layers in a dense block. Layer-to-layer feed-forward connections in DenseNets promote feature reuse. This

5) design has yielded promising skin cancer classification findings [23].

6) The U-Net Many segmentation tasks use this architecture to segment skin lesions. It has a constricted path for precise localization and an extending path for context capture [24].

7) Capsule networks (CapsNets) address CNN problems in handling feature hierarchies. CapsNets are less popular in dermatology than CNNs, but they can identify hierarchical structures in medical images [25].

8) The VGG is a convolutional neural network (CNN) architecture developed at the University of Oxford, known for its efficacy and ease of use in image recognition applications. Due to their deep architecture and ability to capture minute information, VGG models have been used to extract and classify skin lesion images to identify and classify skin cancer types [8].

9) MobileNet, a lightweight CNN architecture, effectively classifies skin lesions due to its compatibility with low-resource devices like cell phones [10].

V. Performance Comparison and Accuracy of Models

Table 1 shows the comparative performance of the techniques discussed in this review paper. We have included only deep learning models as well as presented the best accuracy found in the review paper in Table 1.

TABLE I . PERFORMANCE COMPARISON AND ACCURACY OF MODELS

Years	Authors	Model	Accuracy	Contribution
2023	[26]	AlexNet, VGG-16, VGG-19	Accuracy = 98.33%, F1 score = 0.96	Eight CNN models that had been trained beforehand were used to classify dermoscopy images.
2023	[27]	Deep residual network	Accuracy = 96.971%, F1-score = 0.95	Skin cancer images were classified using a deep residual neural network focused on wavelet transform.
2022	[28]	Squeeze-MNet	Accuracy = 99.36%	To classify photos of skin cancer on Internet of Things devices, a lightweight model was presented.
2023	[29]	ResNet-101 with SVM	Accuracy = 96.15% (ISIC 2019), 97.15% (ISIC 2020)	Features from images of skin cancer were extracted using a multi-stage deep model.
2022	[30]	CNN, pre-trained VGG-16, Xception, ResNet 50	Accuracy = 88% (VGG-16), F1-score = 0.88 (VGG-16)	Skin cancer datasets were used to assess the performances of several deep learning as well as machine learning methods.
2022	[31]	Inceptionv313, ResNet5014, 170 MobileNetv23, EfcientNet15, BYOL16, SwAV	Class prediction Probability = 1.00 (Mel)	A web server with CNN functionality was created to identify skin tumors.
2022	[6]	SkinNet-16	Accuracy = 95.51% HAM10000), 99. 9% (ISIC)	Suggested using CNN to classify skin tumors, called SkiNet-16. Features were chosen using PCA.

2022	[19]	thirteen CNN architectures with DensNet201	Accuracy = 82.9%, F1-score = 0.744	13 different transfer learning models were examined for the categorization of skin carcinomas.
2023	[12]	DenseNet201	95.07%	Employ DenseNet121, DenseNet169, and DenseNet201, three cutting-edge deep convolutional neural network (CNN) models, to more precisely identification and categorize the many types of skin cancer.
2020	[22]	CNN	98.89%	The suggested technique for classifying images of skin cancer uses convolutional neural networks

VI. Conclusions

Deep learning for skin tumor diagnosis could transform medicine. A comprehensive literature evaluation shows that these technologies can help dermatologists and other professionals diagnose and treat diseases early. Image-based and deep learning algorithms increase skin illness and cancer diagnosis. Its capacity to learn from huge datasets improves classification accuracy for all skin types and demographics. Deep learning architectures and algorithms for skin cancer detection and classification were our emphasis. This review examined deep learning approach performance and computational cost. Deep learning systems can't diagnose skin cancer well without large skin lesion datasets. Since most skin lesion datasets feature white skin, testing deep learning models on skin tones reduces accuracy. Future skin lesion databases may have many skin tones to study color prejudice. Deep learning hardware is needed for real-time dermatological assistance. Big, diverse, high-quality datasets, clinical generalization, and interpretability are needed. Deep learning-based skin cancer detection systems must overcome these challenges to be clinically applicable. Clinical, research, and technical specialists must collaborate to improve, analyze, and ethically employ these models. Deep learning and overcoming restrictions could improve dermatology and skin cancer diagnosis.

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