Skin cancer diagnosis using the deep learning advancements: a technical review

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ABSTRACT

It is vital in today's technologically advanced society to combat skin cancer using machines rather than human intervention. Any time the look of the skin changes abnormally, there is a danger that the person might be at risk for skin cancer. Dermatology expertise and computer vision methods must be merged to diagnose melanoma more effectively. Because of this, it is necessary to learn about numerous detection methods to help doctors discover skin cancer at an early stage. This research paper provides a comprehensive technical review of the advancements in using deep learning techniques for the diagnosis of skin cancer. Since skin cancer is so prevalent, early identification is essential for better treatment results. Among the medical uses where deep learning, a kind of machine learning, has shown promise is in the identification of skin cancer. This research investigates the most cutting-edge skin cancer diagnostic deep-learning approaches, datasets, and assessment metrics currently in use. This study discusses the benefits and drawbacks of using deep learning for skin cancer detection. Challenges include ethical and privacy considerations about patient data, the incorporation of models into clinical procedures, and problems with dataset bias and generalisation.

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1. INTRODUCTION

Skin malignancies are becoming more common and deadly across the world. Skin cancer is linked to overexposure to the sun's ultraviolet (UV) rays [1]. Regardless, the World Health Organization (WHO) claims that 30% of all newly diagnosed cancers are caused by sun exposure [2]. Skin cancer is a common and sometimes fatal illness that is on the rise everywhere. Accurate and prompt diagnosis is critical for successful therapy and better patient outcomes. The problem with using dermatologists' eyes to diagnose skin cancer is that it's subjective and prone to human mistakes. As a result, there has been a rise in research into using deep learning for automated skin cancer detection.

Humans are made up of living cells that divide and die. In the human body, cell division replaces dying cells. Cancer is caused by uncontrolled cell division. Human skin cancer is caused by aberrant cell growth that may invade and spread to other parts of the body. Skin cancer is classified as basal cell carcinoma (BCC), squamous cell carcinoma (SCC), or melanoma (MEL) [3]. The rarest kind, melanoma, is the deadliest owing to metastasis. While BCC and SCC are the most prevalent non-melanoma skin cancers (NMSC) [4].

If found early, 90% of skin cancers may be cured, compared to just 50% if identified late [5]. Modern noninvasive imaging techniques have improved in-situ skin cancer detection. Melanoma's poor diagnostic accuracy may lead to overtreatment and undertreatment, which can lead to both (caused by false negative diagnosis). For biopsy and pathological examination, many benign lesions must be removed, which increases treatment expenses. High-resolution magnetic resonance imaging (MRI)s, for example, may minimize excisions and their associated costs by improving diagnostic specificity. Many imaging techniques are used to diagnose skin cancer including reflection confocal microscopy, optical coherence tomography, ultrasound, and dermoscopy [6].

This kind of skin cancer starts in the melanocytes, which control the skin's color. Figure 1 shows melanoma cells that have penetrated further into the skin. Skin cancer incidence rates are rising, with 5.4 million new cases of squamous cell carcinoma diagnosed each year in the US [7].

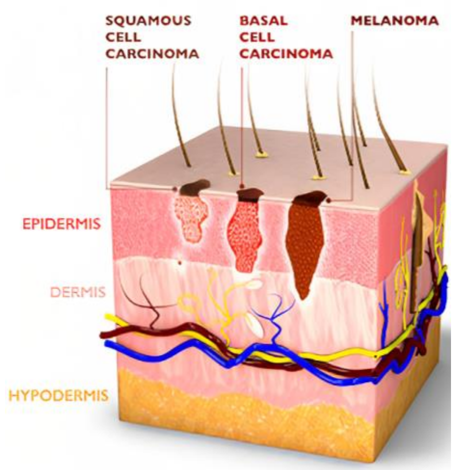

Figure 1. Type of skin cancers

This technical review aims to explore and evaluate the current state-of-the-art deep learning methodologies employed in skin cancer diagnosis. By critically examining the existing research and advancements in this field, we seek to provide insights into the strengths, limitations, and potential avenues for improvement in utilizing deep learning techniques for accurate and efficient skin cancer diagnosis.

This paper adds to deep learning studies on skin cancer diagnosis. We wish to offer a complete picture of the existing environment and motivate future studies to overcome the limits and advance the topic by showing the pros and downsides of current methodologies. Our goal is to construct reliable, interpretable, and therapeutically usable deep-learning models for skin cancer detection to improve patient outcomes and save lives. The following is a list of the major goals that this research study aims to accomplish:

- To examine cutting-edge deep learning approaches used for skin cancer diagnosis: the goal of this work is to summarise the current state of the art in skin cancer diagnostics using deep learning architectures and methods. Our mission is to analyze the strengths and weaknesses of these methods in properly diagnosing skin lesions and differentiating benign from malignant tumors.
- To discuss the challenges and limitations of deep learning-based skin cancer diagnosis: in this study, we'll look at the problems and restrictions of using deep learning methods to diagnose skin cancer. Dataset bias, model generalization, a lack of interpretability and explainability, ethical concerns, and difficulty to integrate with clinical processes are all potential problems.
- To propose potential directions for future research and improvements: based on the analysis of the current state-of-the-art, this research paper will suggest potential areas for future research and improvements in deep learning-based skin cancer diagnosis. These may include the development of explainable deep learning models, strategies to enhance model robustness and generalization, multi-modality fusion for improved diagnosis, and validation of models in real-world clinical settings.

This study intends to accomplish these ends by providing a detailed technical overview of the developments made utilizing deep learning methods for skin cancer detection. The ultimate goal is to improve accurate and efficient skin cancer detection by applying for deep learning advances, and this paper aims to provide light on the existing environment, obstacles, and future research prospects in this dynamic subject.

Method: for published original research, we combed through the databases of ScienceDirect (including PubMed), Elsevier (including Web of Science), and Web of Science (including Google Scholar). We only included publications in our evaluation that had enough data and information about the research methodology they used. Only studies that demonstrate adequate scientific progress are considered for inclusion in this study. This study excludes works in which the performance's genesis is implausible.

Outline of the paper: the remaining part of the paper is organized as follows: section 2 reviews the various segmentation techniques that can be appropriate for dermoscopy images. Section 3 throws light on fundamental concepts of deep learning. This section also focuses on various deep learning-based classification methods. Section 4 discusses the challenges and limitations of deep learning-based skin cancer diagnosis. Section 5 discusses future directions and research opportunities. Finally, section 6 concludes the paper.

2. SEGMENTATION TECHNIQUES FOR DERMOSCOPY IMAGES

There is a lot of discussion in this section on various strategies for segmenting the lesion area in dermoscopic pictures that can be found in numerous publications.

Ashour *et al*. [8] created a technique that employs histogram-based clustering estimation (HBCE) and neutrosophic c-means clustering (NCM) for dermoscopy photographs to identify skin lesions. HBCE uses h-v and v-h calculations. This solution is trained on 900 photographs and is tested with 379 images. In contrast to NCM without HBCE, the suggested study demonstrates superior outcomes than the typical NCM technique.

Automated lesion segmentation employing two phases of pre-processing and segmentation has been proposed by Jaisakthi *et al*. [9]. Bi-linear interpolation is used for picture scaling in the pre-processing step, and the CLACHE algorithm is used to improve the image's uneven lighting. Hair pixels are replaced using the Frangivesselness filter and FMM inpainting method. Using uniformity in pixel attributes like color and texture, segmentation is used to separate the lesion areas.

The technique proposed by Mahmouei *et al*. [10] named the quad-tree melanoma detection method is a reliable expert color evaluation model that conducts colour observation that can quickly categorize the lesion, either benign or malignant. Melanomas are studied using Euclidean distances and concentric quartiles. Pre-processing enhances lesion-background contrast. Top-hat and bottom-hat surgeries address low-contrast lesions. Segmentation is done in two steps using hybrid thresholding to detect lesion borders. The core lesion region is enlarged using adaptive histogram functions after a modified Otsu threshold determines it. Enactment analysis shows that the classifier SVM performs well with ROC curve attributes.

New meta-heuristic algorithms for finding the best location for humans to shoot deer were developed by Brammya *et al*. [11], using a DHOA-NN method. The buck's visual power is five times greater than that of a person, making the hunting procedure more challenging because of this. It's hard to see what's going on at the very top of the horizon. As a result, the hunters are said to conduct maneuvers in that area. Until the optimal location is found, the goal function is used to execute position updates for each iteration. So, it is determined that in comparison to other current algorithms, DHOA-NN performs better in terms of convergence.

Soudani and Barhoumi [12] offer a segmentation recommender to save training time. The convolution sections of VGG16 and ResNet50 extract features. A CNN classifier has five nodes that reflect segmentation algorithms and build an output layer. Two-dimensional dermoscopy pictures show local details from various places. The result shows that the recommended technique predicts skin lesion segmentation well.

Walker *et al*. [13] use an inception V2 network to classify dermoscopic images. Deep learning trains inception v2 parameters using the stochastic decent gradient. Dermoscopic images provide visual and sonification assessments. Tele-dermoscopy sonification output was more accurate and sensitive for both pigmented and non-pigmented lesions.

Al-Masni *et al*. [14] offer a full-resolution convolution network segmentation technique to analyze every pixel in dermoscopy images. CNNs categorize pixels using cross-entropy loss functions. The convolutional layer approach extracts full-resolution features without pre or post-processing. Backpropagation reduces network training errors.

Wang *et al*. [15] designed BIFSeg to handle many object kinds in one framework. Image-specific fine-tuning using a weighted loss function may adjust a CNN model to a test image. Deep learning-based algorithms segment 2D/3D medical images intuitively. The recommended weighted loss function allows image-specific fine-tuning for both supervised and unsupervised segmentation refinement. By training a neural network (NN) on the bounding box content, similar structures may be discovered across varied items and utilized to generalize hidden object identification. BIFSeg may achieve more accuracy with less user engagement and less time than interactive segmentation approaches.

Segmenting lesions may enhance automated computer-aided melanoma detection methods, according to Ahn *et al*. [16]. Traditional segmentation algorithms struggle to segment skin lesions due to imprecise lesion margins, low contrast between the lesion and adjacent skin, and lesion touching image boundaries. Bayesian analysis improves lesion structure and boundaries. The approach is compared to lesion segmentation and unsupervised saliency detection methods using two public datasets. Thus, the recommended approach beats the alternatives. Saliency-optimization improves lesion segmentation.

3. DEEP LEARNING IN MEDICAL IMAGING

Several algorithms enable deep learning, or deep structured learning [17]. Deep learning, like NN, contains a cascade of levels. Unlike traditional machine learning methods, deep learning can directly extract features from pictures, text, and sound in both supervised and unsupervised settings. This approach incorporates feature extraction with learning. Deep learning reduces the requirement for hand-tuned ML systems [NO_PRINTED_FORM].

The majority of modern deep learning applications depend on transfer learning, especially in the field of computer vision [18], [19]. By using a model that was developed for one task and then applied to another, this technique is known as "transfer learning". Computer vision challenges in the medical field, such as skin cancer diagnosis, often have insufficient datasets and need a lot of effort to train a neural network from scratch. The use of an initialization network trained on a big dataset (like ImageNet's 1.2 million pictures) is typical because of this.

It is usual to use supervised learning to train convolutional neural networks (CNNs), which are deep neural networks optimized for image processing. Using labelled data such as dermoscopic pictures and their related diagnosis/ground truth, CNNs may infer a link between the input data and labels. Thus, CNNs may apply learnt operations to new pictures and categorize them using the characteristics they extract. The application of CNNs in clinical dermatology and dermatopathology might aid in the development of new and/or enhanced clinically relevant DBs, since diagnosis in these fields relies heavily on visual pattern recognition [20].

3.1. Skin cancer classification using deep learning

Using skin cancer photos for deep learning may help clinicians distinguish between various forms of skin cancer. To detect skin cancer, doctors just snap a photo of the patient and run it through a deep learning architecture (such as MobileNet) [21]. Because of this, deep learning may help diagnose without the need for additional lab tests or costs. However, it is critical to have a well-developed and precise teaching model. When computational power is limited, an architecture like MobileNet is a preferable option for visual applications on mobile devices and in the cloud. A simplified design that builds lightweight deep neural networks utilizing highly separable convolutions is what makes MobileNets important [22], [23].

Deep learning models are now being used to analyze medical data. Skin cancer detection has resulted in a wide range of models. When it comes to neural networks, Yu *et al*. [24] have developed a deep one that can learn even when there is only a limited amount of training data. GoogleNet CNN architecture [25] was used by Esteva *et al*. [26] in order to train over 120 thousand images and achieve a dermatologist-level diagnosis. They, like Haenssle [27] *et al.* and Brinker *et al.* [28], employed pre-trained models to compare dermatologists' performance.

Table 1 presents a performance comparison of various deep-learning methods for skin cancer diagnosis. The evaluation metric used to measure the performance of these methods is accuracy, which represents the overall classification accuracy of the models. The table further breaks down the accuracy percentages for each deep-learning method across different classes of skin cancer: benign, malignant, and melanoma. These percentages provide insights into the performance of the models in correctly identifying each class.

3.2. Skin classification using transfer learning

In the absence of easily available datasets, transfer learning is often employed to categorize skin lesions. First, a CNN is trained on ImageNet, then its weighting parameters are changed to meet the classification task.

Esteva *et al*. [26] made a significant contribution to the field. Total 129,450 photos were used to train the CNN model, including 3374 images taken from dermatoscopic equipment and representing 2032 distinct skin lesions for the first time. Malignant melanomas were compared to benign nevi, while keratinocyte carcinomas were compared to benign seborrheic keratosis. Both of these comparisons were considered as binary classification challenges. The final categorization differentiation was determined for both clinical and dermatoscopic images. The inception v3 model trained on the ImageNet database was used to categorize images. The CNN model for skin lesion categorization was fine-tuned using transfer learning. A novel tree-structured disease taxonomy is used in this method, with each ailment represented by a leaf. In the inner nodes, a group of illnesses with comparable anatomical and clinical features may be found. In a higher-level tree, the probability of child nodes in the coarser lesion class is totaled together (i.e., an inner node). CNNs trained to recognize cancers and melanomas were evaluated using biopsy-proof data and attained ROC AUCs of 0.96 and 0.96 for carcinomas and 0.94 and 0.94 for melanomas, respectively, based on dermatoscopic pictures.

Table 1. Performance comparison of deep learning methods for skin cancer diagnosis

Methods	No of classes	Accuracy in percentage		
CNN [29]	3	90	81	84
SSDMobilenet model [30]	2	99	100	
Incorporate background knowledge [31]	1	80.39		
CNNs [32]	2	83.83	97.55	
Transfer learning [33]	1	98.33		
CNN [34]	3	82.26	88.82	90.40
CNN [26]	2	69.4	72.1	
CNNs [35]		90.96	97.00	97.60
Multi-scale CNN [36]	1	90.3		
Automated computer-aided model CNN [37]	1	11		
CNN [38]	1	81.8		
VGG-16 CNN [39]	1	78		

The scientific openness shown by Han *et al*. [40] is especially significant since their computer program has been made freely accessible for external examination. Based on clinical photos, the researchers developed a classification system for 12 distinct skin conditions. With the help of 19,398 training photos, they created a ResNet model. An AUC of 0.96, 0.83, 0.82, and 0.96 was reached using publically accessible Asan datasets for BC, SCC, and IEC.

According to Marchetti *et al*. [41], a collection of CNNs can be used to distinguish between melanomas and nevi or lentigines. For the ISBI 2016 Challenge, authors combined all 25 participating teams' automatic predictions into a single categorization using five approaches. They compared two non-learning and three machine-learning techniques. The ensemble method with the highest average precision, greedy fusion, had a sensitivity of 58% and a specificity of 88%.

Kawahara and Hamarneh [38] describe a new design for a CNN ensemble. In CNN, each part of the network saw the same picture at a slightly different resolution. Afterward, a single layer is created by combining the output of several resolutions. End-to-end learning optimizes the weighting parameters of the CNN, which detects interactions between images of varying resolutions. On average, in the Dermofit Image Library, the algorithm correctly classified 79.5% of the images.

Esteva *et al*. [26] and Sun *et al.* [42] proposed a classifier with 198 highly precisely specified training classes. CaffeNet and VGGNet CNN models were trained and tested on a total of 6584 clinical photos from the DermQuest image database, and their classification performance was assessed. The pretrained VGGNet with optimal weighting settings has the best average accuracy of 50.27% across all 198 classes.

4. CHALLENGES AND LIMITATIONS

In recent years, skin cancer detection has been an area where deep learning approaches have shown considerable potential. With these advancements, we may see a dramatic change in how we diagnose and manage this potentially fatal illness. These developments hold great promise, but they are also accompanied by a number of obstacles that must be surmounted before deep learning may be used responsibly and effectively in therapeutic settings. Understanding and overcoming these issues is crucial for the safe and successful use of deep learning in therapeutic settings. In order to overcome these challenges, researchers, physicians, legislators, and regulatory authorities will need to work together. Further study is required to improve deep learning models in skin cancer detection with regards to interpretability, generalizability, and ethical aspects. By addressing these obstacles, we may realise deep learning's full potential in enhancing skin cancer detection in terms of precision, speed, and accessibility, eventually leading to improved patient outcomes. The following are key challenges and limitations associated with the application of deep learning in skin cancer diagnosis:

4.1. Dataset bias and generalization issues

When developing deep learning models for medical image analysis, it's essential to address potential dataset biases and generalization issues to ensure the models perform reliably and equitably across diverse populations and real-world scenarios. These challenges can arise due to various factors, including:

- Limited diversity and representativeness of datasets: the availability of high-quality, diverse, and well-annotated datasets are crucial for training robust deep learning models. However, existing datasets may suffer from biases, such as under-representation of certain skin types or ethnicities, leading to reduced generalization and potential performance disparities in real-world scenarios [43].
- Domain shift: deep learning models trained on specific datasets may struggle to generalize well to new, unseen data. Changes in imaging devices, image resolutions, or demographics of patients can introduce domain shifts, affecting the model's performance. Ensuring model robustness and generalization across different populations and data sources remains a challenge [44].

4.2. Lack of explainability and interpretability

Despite impressive performance of deep learning models, their complex nature often makes it challenging to understand the underlying decision-making process, which can hinder trust and adoption in clinical settings. Addressing these challenges is an active area of research, focusing on:

- Black box nature of deep learning models: as a result of the difficulty in interpreting and explaining the decision-making process caused by deep learning models, they are sometimes referred to as "black boxes". The lack of transparency may limit the clinical adoption of deep learning in skin cancer diagnosis, as clinicians require explanations and insights to gain trust and confidence in the model's predictions [45].
- Model interpretability methods: while research on interpretable deep learning techniques is advancing, there is a need for standardized approaches to explain the decisions made by deep learning models in skin cancer diagnosis. Developing methods to provide transparent explanations and highlighting the salient features driving the model's predictions is an ongoing research area [46].

4.3. Ethical and privacy concerns

Key areas of focus related with ethical, and privacy of deep learning models include:

- Data privacy and security: deep learning models often rely on large amounts of sensitive patient data, raising concerns about data privacy and security. Safeguarding patient information and complying with ethical guidelines and regulations, such as data anonymization and informed consent, are critical for responsible research and deployment [47].
- Bias and fairness: deep learning models can inadvertently perpetuate biases present in the training data, leading to potential disparities in diagnosis across different demographics. Addressing bias and ensuring fairness in skin cancer diagnosis is crucial to prevent inequities in healthcare delivery.

4.4. Integration with clinical workflows

Successful deployment of deep learning models for skin cancer diagnosis hinges on following facts:

- Real-world deployment and integration: integrating deep learning models into clinical workflows poses practical challenges. Ensuring seamless integration, scalability, and compatibility with existing healthcare systems and processes is essential for effective implementation [48].
- Clinical validation and regulatory approval: deep learning models for skin cancer diagnosis need to undergo rigorous clinical validation to demonstrate their safety, efficacy, and superiority over existing diagnostic methods. Obtaining regulatory approvals and certifications is crucial for widespread clinical adoption.

Addressing these challenges and limitations will require collaborative efforts from researchers, clinicians, policymakers, and regulatory bodies. Continued research and development are necessary to enhance the interpretability, generalization, and ethical considerations of deep learning models in skin cancer diagnosis. By mitigating these challenges, we can unlock the full potential of deep learning to improve the accuracy, efficiency, and accessibility of skin cancer diagnosis, leading to better patient outcomes.

5. FUTURE DIRECTIONS AND RESEARCH OPPORTUNITIES

The field of skin cancer diagnosis using deep learning advancements is rapidly evolving, offering several exciting avenues for future research and improvements. The following are potential directions and research opportunities that can further enhance the accuracy, interpretability, and clinical applicability of deep learning models in skin cancer diagnosis.

5.1. Explainable deep learning for skin cancer diagnosis

There is a growing need to develop techniques that can provide transparent and understandable explanations for their predictions. Key areas of focus in this domain include:

- Development of interpretable deep learning models: advancements in explainable AI techniques can enable deep learning models to provide transparent and understandable explanations for their predictions in skin cancer diagnosis. Research efforts should focus on developing models that highlight important features and provide insights to aid clinicians in decision-making processes.
- Model-agnostic interpretability methods: exploring model-agnostic interpretability methods, such as saliency maps, attention mechanisms, and feature attribution techniques, can help in understanding the reasoning behind the deep learning models' predictions. These methods can provide additional confidence and trust in the model's decisions.

5.2. Robustness and generalization of deep learning models

Deep learning models need to be resilient against adversarial attacks and capable of adapting to different domains and real-world scenarios. Addressing these challenges involves:

- Adversarial robustness: investigating adversarial attacks and defense mechanisms to enhance the robustness of deep learning models against adversarial examples specific to skin cancer diagnosis. This can help improve the model's performance under various perturbations and ensure reliable predictions in real-world scenarios.
- Domain adaptation and transfer learning: exploring domain adaptation techniques to address the challenges of domain shift and generalize deep learning models across different populations, imaging devices, and datasets. The effectiveness of models used for diagnosing skin cancer may be enhanced by exploring transfer learning strategies that draw on expertise from comparable activities or domains.

5.3. Multi-modality fusion for enhanced diagnosis

This multi-modality fusion approach aims to followings:

- Integration of multiple imaging modalities: to better diagnose skin cancer, researchers are looking at combining data from many sources such as dermoscopy pictures, histopathology slides, and clinical data. The diagnostic accuracy of a system may be improved by the use of multi-modal fusion, which provides additional data from several sources.
- Integration of non-imaging data: learning more about how to include patient-specific data (such as demographics, health records, genetic information, and environmental variables) into skin cancer diagnosis models. A more precise and personalized diagnosis is possible because of a more comprehensive patient history being taken into account.

5.4. Clinical validation and real-world deployment

The effectiveness and generalizability of deep learning models for skin cancer detection need to be validated in large-scale clinical research across different sites. The results of these investigations may provide credence to the usefulness of the models and help lead their adoption into standard clinical practice.

- Prospective studies and real-world deployment: assessing the effects of deep learning models on clinical outcomes, patient management, and healthcare processes, as well as evaluating their effectiveness in real-world clinical situations. The potential benefits and drawbacks of incorporating deep learning into standard clinical treatment may be better understood via prospective research.
- Future progress in the use of deep learning for skin cancer detection may be made by concentrating on the aforementioned areas and topics for study. Researchers, physicians, and other stakeholders must work together to advance deep-learning models for skin cancer detection, overcome current obstacles, and assure their appropriate and successful use.

6. CONCLUSION

In this in-depth technical review, we have looked at how deep learning has helped with skin cancer detection. This research explores many segmentation methods well-suited to dermoscopy pictures, stressing their significance in locating and outlining skin lesions. We then dove into the core ideas of deep learning, illuminating its potential to transform the way skin cancer is diagnosed. To effectively categorize skin lesions and differentiate between benign and malignant cancers, this review included a wide variety of deep learning-based classification approaches.

While deep learning shows significant potential, it is important to recognize the difficulties and constraints that come with using it to diagnose skin cancer. Issues with bias in datasets, interpretability, ethics, and incorporating findings into clinical processes were highlighted. These challenges necessitate concerted efforts to address them, ensuring the responsible and effective utilization of deep learning models in clinical practice.

Looking towards the future, our exploration of future directions and research opportunities highlights avenues for further improvement in skin cancer diagnosis. The development of explainable deep learning models can enhance transparency and understanding, fostering trust in the decision-making process. Robustness and generalization of deep learning models can be achieved through adversarial defense mechanisms and domain adaptation techniques. The integration of multiple imaging modalities and patient-specific data holds promise for enhanced diagnostic accuracy and personalized care.

By acknowledging these challenges and pursuing future research directions, we can overcome the limitations of deep learning-based skin cancer diagnosis and unlock its full potential. Collaborative efforts among researchers, clinicians, and stakeholders are vital to drive innovation, ensure ethical considerations, and validate the clinical applicability of deep learning models.

REFERENCES

[1] P. Rutkowski *et al.*, "Expert recommendation on diagnostic - therapeutic management in skin carcinomas," *Oncology in Clinical Practice*, vol. 18, no. 2, pp. 69–91, Apr. 2022, doi: 10.5603/OCP.2021.0032.

[2] C. Barata, M. E. Celebi, and J. S. Marques, "A Survey of Feature Extraction in Dermoscopy Image Analysis of Skin Cancer," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 3, pp. 1096–1109, May 2019, doi: 10.1109/JBHI.2018.2845939.

[3] F. Ulutaş, E. Çomut, and V. Çobankara, "Development of Two Types of Skin Cancer in a Patient with Systemic Sclerosis: a Case Report and Overview of the Literature," *Case Reports in Oncological Medicine*, vol. 2021, pp. 1–5, Feb. 2021, doi: 10.1155/2021/6628671.

[4] D. Ost, C. Joseph, H. Sogoloff, and G. Menezes, "Primary pulmonary melanoma: Case report and literature review," *Mayo Clinic Proceedings*, vol. 74, no. 1, pp. 62–66, Jan. 1999, doi: 10.4065/74.1.62.

[5] F. Bray, J. Ferlay, I. Soerjomataram, R. L. Siegel, L. A. Torre, and A. Jemal, "Estimates of incidence and mortality worldwide for 36 cancers in 185 countries," *CA: A Cancer Journal for Clinicians*, vol. 68, no. 6, pp. 394–424, 2018.

[6] H. D. Heibel, L. Hooey, and C. J. Cockerell, "A Review of Noninvasive Techniques for Skin Cancer Detection in Dermatology," *American Journal of Clinical Dermatology*, vol. 21, no. 4, pp. 513–524, Aug. 2020, doi: 10.1007/s40257-020-00517-z.

[7] P. Aggarwal, P. Knabel, and A. B. Fleischer, "United States burden of melanoma and non-melanoma skin cancer from 1990 to 2019," *Journal of the American Academy of Dermatology*, vol. 85, no. 2, pp. 388–395, Aug. 2021, doi: 10.1016/j.jaad.2021.03.109.

[8] A. S. Ashour, Y. Guo, E. Kucukkulahli, P. Erdogmus, and K. Polat, "A hybrid dermoscopy images segmentation approach based on neutrosophic clustering and histogram estimation," *Applied Soft Computing Journal*, vol. 69, pp. 426–434, Aug. 2018, doi: 10.1016/j.asoc.2018.05.003.

[9] S. M. Jaisakthi, P. Mirunalini, and C. Aravindan, "Automated skin lesion segmentation of dermoscopic images using GrabCut and kmeans algorithms," *IET Computer Vision*, vol. 12, no. 8, pp. 1088–1095, 2018, doi: 10.1049/iet-cvi.2018.5289.

[10] S. S. Mahmouei, M. Aldeen, W. V. Stoecker, and R. Garnavi, "Biologically Inspired QuadTree Color Detection in Dermoscopy Images of Melanoma," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 2, pp. 570–577, Mar. 2019, doi: 10.1109/JBHI.2018.2841428.

[11] G. Brammya, S. Praveena, N. S. N. Preetha, R. Ramya, B. R. Rajakumar, and D. Binu, "Deer Hunting Optimization Algorithm: A New Nature-Inspired Meta-heuristic Paradigm," *Computer Journal*, vol. 133, no. 1, May 2019, doi: 10.1093/comjnl/bxy133.

[12] A. Soudani and W. Barhoumi, "An image-based segmentation recommender using crowdsourcing and transfer learning for skin lesion extraction," *Expert Systems with Applications*, vol. 118, pp. 400–410, Mar. 2019, doi: 10.1016/j.eswa.2018.10.029.

[13] B. N. Walker *et al.*, "Dermoscopy diagnosis of cancerous lesions utilizing dual deep learning algorithms via visual and audio (sonification) outputs: Laboratory and prospective observational studies," *EBioMedicine*, vol. 40, pp. 176–183, Feb. 2019, doi: 10.1016/j.ebiom.2019.01.028.

[14] M. A. Al-Masni, M. A. Al-Antari, M. T. Choi, S. M. Han, and T. S. Kim, "Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks," *Computer Methods and Programs in Biomedicine*, vol. 162, pp. 221–231, Aug. 2018, doi: 10.1016/j.cmpb.2018.05.027.

[15] G. Wang *et al.*, "Interactive Medical Image Segmentation Using Deep Learning with Image-Specific Fine Tuning," *IEEE Transactions on Medical Imaging*, vol. 37, no. 7, pp. 1562–1573, Jul. 2018, doi: 10.1109/TMI.2018.2791721.

[16] E. Ahn *et al.*, "Saliency-Based Lesion Segmentation Via Background Detection in Dermoscopic Images," *IEEE Journal of Biomedical and Health Informatics*, vol. 21, no. 6, pp. 1685–1693, Nov. 2017, doi: 10.1109/JBHI.2017.2653179.

[17] R. G. Tiwari, A. Misra, V. Khullar, A. K. Agarwal, S. Gupta, and A. P. Srivastava, "Identifying Microscopic Augmented Images using Pre-Trained Deep Convolutional Neural Networks," in *Proceedings of International Conference on Technological Advancements and Innovations, ICTAI 2021*, IEEE, Nov. 2021, pp. 32–37, doi: 10.1109/ICTAI53825.2021.9673472.

[18] A. K. Agarwal, R. G. Tiwari, V. Khullar, and R. K. Kaushal, "Transfer Learning Inspired Fish Species Classification," in *Proceedings of the 8th International Conference on Signal Processing and Integrated Networks, SPIN 2021*, IEEE, Aug. 2021, pp. 1154–1159, doi: 10.1109/SPIN52536.2021.9566067.

[19] R. G. Tiwari, V. Khullar, and K. D. Garg, "Web Recommendation by Exploiting User Profile and Collaborative Filtering," *Lecture Notes in Electrical Engineering*, vol. 832, pp. 335–345, 2022, doi: 10.1007/978-981-16-8248-3_27.

[20] R. G. Tiwari, M. Husain, B. Gupta, and A. Agrawal, "Amalgamating contextual information into recommender system," in *Proceedings - 3rd International Conference on Emerging Trends in Engineering and Technology, ICETET 2010*, IEEE, Nov. 2010, pp. 15–20, doi: 10.1109/ICETET.2010.110.

[21] W. Wang, Y. Li, T. Zou, X. Wang, J. You, and Y. Luo, "A novel image classification approach via dense-mobilenet models," *Mobile Information Systems*, vol. 2020, pp. 1–8, Jan. 2020, doi: 10.1155/2020/7602384.

[22] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, IEEE, Jun. 2018, pp. 4510–4520, doi: 10.1109/CVPR.2018.00474.

[23] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," *2017 IEEE*

Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 2261-2269, doi: 10.1109/CVPR.2017.243.

[24] Z. Yu *et al.*, "Melanoma Recognition in Dermoscopy Images via Aggregated Deep Convolutional Features," *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 4, pp. 1006–1016, Apr. 2019, doi: 10.1109/TBME.2018.2866166.

[25] L. Balagourouchetty, J. K. Pragatheeswaran, B. Pottakkat, and G. Ramkumar, "GoogLeNet-Based Ensemble FCNet Classifier for Focal Liver Lesion Diagnosis," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 6, pp. 1686–1694, Jun. 2020, doi: 10.1109/JBHI.2019.2942774.

[26] A. Esteva *et al.*, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, Feb. 2017, doi: 10.1038/nature21056.

[27] H. A. Haenssle *et al.*, "Man against Machine: Diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists," *Annals of Oncology*, vol. 29, no. 8, pp. 1836–1842, Aug. 2018, doi: 10.1093/annonc/mdy166.

[28] T. J. Brinker *et al.*, "Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task," *European Journal of Cancer*, vol. 113, pp. 47–54, May 2019, doi: 10.1016/j.ejca.2019.04.001.

[29] J. O. Emuoyibofarhe and D. Ajisafe, "Early Skin Cancer Detection Using Deep Convolutional Neural Networks on Mobile Smartphone," *International Journal of Information Engineering and Electronic Business*, vol. 12, no. 2, pp. 21–27, Apr. 2020, doi: 10.5815/ijieeb.2020.02.04.

[30] A. M. Taqi, F. Al Azzo, M. Milanova, F. Al-Azzo, and A. Awad, "Skin Lesion Detection by Android Camera based on SSD-Mo-bilenet and TensorFlow Object Detection API Deep Learning and medical applications View project Deep learning technique View project Skin Lesion Detection by Android Camera based on SSD-Mo-bilenet and TensorFlow Object Detection API," *Article in Journal of Advanced Research*, vol. 2019, pp. 6–12, 2019.

[31] K. Sriwong, S. Bunrit, K. Kerdprasop, and N. Kerdprasop, "Dermatological classification using deep learning of skin image and patient background knowledge," *International Journal of Machine Learning and Computing*, vol. 9, no. 6, pp. 862–867, Dec. 2019, doi: 10.18178/ijmlc.2019.9.6.884.

[32] A. Mahbod, G. Schaefer, I. Ellinger, R. Ecker, A. Pitiot, and C. Wang, "Fusing fine-tuned deep features for skin lesion classification," *Computerized Medical Imaging and Graphics*, vol. 71, pp. 19–29, Jan. 2019, doi: 10.1016/j.compmedimag.2018.10.007.

[33] K. M. Hosny, M. A. Kassem, and M. M. Foaud, "Skin Cancer Classification using Deep Learning and Transfer Learning," in *2018 9th Cairo International Biomedical Engineering Conference, CIBEC 2018 - Proceedings*, IEEE, Dec. 2018, pp. 90–93, doi: 10.1109/CIBEC.2018.8641762.

[34] E. M. Rogers, K. L. Connolly, K. S. Nehal, S. W. Dusza, A. M. Rossi, and E. Lee, "Comorbidity scores associated with limited life expectancy in the very elderly with nonmelanoma skin cancer," *Journal of the American Academy of Dermatology*, vol. 78, no. 6, pp. 1119–1124, Jun. 2018, doi: 10.1016/j.jaad.2017.12.048.

[35] L. Bi, J. Kim, E. Ahn, D. Feng, and M. Fulham, "Semi-automatic skin lesion segmentation via fully convolutional networks," in *Proceedings - International Symposium on Biomedical Imaging*, IEEE, Apr. 2017, pp. 561–564, doi: 10.1109/ISBI.2017.7950583.

[36] T. DeVries and D. Ramachandram, "Skin Lesion Classification Using Deep Multi-scale Convolutional Neural Networks," *arXiv*, 2017, doi: 10.48550/arXiv.1703.01402.

[37] D. A. Shoieb, S. M. Youssef, and W. M. Aly, "Computer-Aided Model for Skin Diagnosis Using Deep Learning," *Journal of Image and Graphics*, pp. 122–129, 2016, doi: 10.18178/joig.4.2.122-129.

[38] J. Kawahara and G. Hamarneh, "Multi-resolution-tract CNN with hybrid pretrained and skin-lesion trained layers," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2016, pp. 164–171, doi: 10.1007/978-3-319-47157-0_20.

[39] S. Kalouche, "Vision-Based Classification of Skin Cancer using Deep Learning," *Stanford's MachineLearning course (CS 229)*, 2016.

[40] S. S. Han, M. S. Kim, W. Lim, G. H. Park, I. Park, and S. E. Chang, "Classification of the Clinical Images for Benign and Malignant Cutaneous Tumors Using a Deep Learning Algorithm," *Journal of Investigative Dermatology*, vol. 138, no. 7, pp. 1529–1538, Jul. 2018, doi: 10.1016/j.jid.2018.01.028.

[41] M. A. Marchetti *et al.*, "Results of the 2016 International Skin Imaging Collaboration International Symposium on Biomedical Imaging challenge: Comparison of the accuracy of computer algorithms to dermatologists for the diagnosis of melanoma from dermoscopic images," *Journal of the American Academy of Dermatology*, vol. 78, no. 2, pp. 270-277.e1, Feb. 2018, doi: 10.1016/j.jaad.2017.08.016.

[42] X. Sun, J. Yang, M. Sun, and K. Wang, "A benchmark for automatic visual classification of clinical skin disease images," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 9910 LNCS, pp. 206–222, 2016, doi: 10.1007/978-3-319-46466-4_13.

[43] M. Tsuneki, "Deep learning models in medical image analysis," *Journal of Oral Biosciences*, vol. 64, no. 3, pp. 312–320, Sep. 2022, doi: 10.1016/j.job.2022.03.003.

[44] K. Stacke, G. Eilertsen, J. Unger, and C. Lundstrom, "Measuring Domain Shift for Deep Learning in Histopathology," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 2, pp. 325–336, Feb. 2021, doi: 10.1109/JBHI.2020.3032060.

[45] X. Li *et al.*, "Interpretable deep learning: interpretation, interpretability, trustworthiness, and beyond," *Knowledge and Information Systems*, vol. 64, no. 12, pp. 3197–3234, 2022, doi: 10.1007/s10115-022-01756-8.

[46] L. Moss, D. Corsar, M. Shaw, I. Piper, and C. Hawthorne, "Demystifying the Black Box: The Importance of Interpretability of Predictive Models in Neurocritical Care," *Neurocritical Care*, vol. 37, no. 2, pp. 185–191, 2022, doi: 10.1007/s12028-022-01504-4.

[47] S. Kumar *et al.*, "Novel Method for Safeguarding Personal Health Record in Cloud Connection Using Deep Learning Models," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–14, Mar. 2022, doi: 10.1155/2022/3564436.

[48] K. Swanson, E. Wu, A. Zhang, A. A. Alizadeh, and J. Zou, "From patterns to patients: Advances in clinical machine learning for cancer diagnosis, prognosis, and treatment," *Cell*, vol. 186, no. 8, pp. 1772–1791, Apr. 2023, doi: 10.1016/j.cell.2023.01.035.

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