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AUTOMATED SKIN CANCER DIAGNOSIS USING DEEP LEARNING: A SYSTEMATIC REVIEW OF STATE-OF-THE-ART ARCHITECTURES, TECHNIQUES AND PERFORMANCE EVALUATION

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Abstract. *This literature survey offers a comprehensive analysis of deep learning techniques for skin cancer diagnosis. Prompt identification is crucial for improving patient survival rates, and deep learning has demonstrated promising results. The survey examines the fundamentals of skin cancer, various neural network architectures, and their classification efficacy. It investigates the application of deep learning models in clinical decision-making and assesses authentic datasets for evaluating skin cancer detection techniques. Training strategies for enhancing deep learning models are delineated. The survey assesses essential performance indicators, including accuracy, precision, recall, and F1-score. This survey underscores the growing importance of deep learning in skin cancer diagnosis, demonstrating its potential to improve the patient experience and advance clinical practice.*

Keywords: convolutional neural networks, classification, melanoma, medical imaging

ZAUTOMATYZOWANA DIAGNOSTYKA RAKA SKÓRY Z WYKORZYSTANIEM GŁĘBOKIEGO UCZENIA: SYSTEMATYCZNY PRZEGLĄD NAJNOWOCZEŚNIEJSZYCH ARCHITEKTUR, TECHNIK I OCENY WYDAJNOŚCI

Streszczenie. *Niniejszy przegląd literatury przedstawia kompleksową analizę technik głębokiego uczenia stosowanych w diagnostyce raka skóry. Wczesne rozpoznanie ma kluczowe znaczenie dla poprawy przeżywalności pacjentów, a głębokie uczenie wykazuje obiecujące wyniki. Artykuł omawia podstawy raka skóry, różne architektury sieci neuronowych oraz ich skuteczność klasyfikacyjną. Analizowane jest zastosowanie modeli głębokiego uczenia w procesie podejmowania decyzji klinicznych oraz ocena rzeczywistych zbiorów danych wykorzystywanych do testowania technik wykrywania raka skóry. Przedstawiono strategie treningowe służące poprawie jakości modeli głębokiego uczenia. W pracy oceniono kluczowe wskaźniki efektywności, takie jak dokładność, precyzja, czułość oraz wskaźnik F1. Przegląd ten podkreśla rosnące znaczenie głębokiego uczenia w diagnostyce raka skóry, ukazując jego potencjał w poprawie usług dla pacjentów i rozwoju praktyki klinicznej.*

Słowa kluczowe: konwolucyjne sieci neuronowe, klasyfikacja, czerniak, obrazowanie medyczne

Introduction

Skin cancer has been one of the most common types of cancer in the last decade [6]. Considering that the skin is the body's largest organ, it is logical to view skin cancer as the most common type of cancer in humans. Skin cancer constitutes roughly 40% of all diagnosed cancer cases. Despite a typical five-year survival rate of approximately 99% for patients with early-stage disease, malignant variants of pigmented skin lesions pose diagnostic challenges owing to their physical similarity to benign forms. In severe cases, the appearance of visual lesion markers is associated with a decrease in survival rates from 68% to 27% [57,86]. Skin cancer is primarily categorized into two principal types: melanoma and non-melanoma skin cancer. Melanoma, a form of cancer, may only be cured if identified early; otherwise, it metastasizes to other regions of the body, resulting in the patient's agonizing demise [23]. The American Cancer Society states that melanoma skin cancer represents only 1% of all cases, although it is linked to a significantly higher mortality rate [54]. Melanoma originates from melanocytes. The process begins when healthy melanocytes undergo uncontrolled proliferation, leading to the formation of a malignant tumour. It can affect any area of the human body. It generally develops in areas exposed to sunlight, such as the hands, face, neck, and lips [62].

Skin cancer comprises several types, with Basal Cell Carcinoma (BCC) and Squamous Cell Carcinoma (SCC) being the most common. Basal cell carcinoma (BCC), constituting around 70–80% of skin cancers, originates in sun-exposed areas and has slow progression with minimal metastatic potential. Squamous cell carcinoma (SCC), accounting for around 20%, displays a more aggressive character and has the potential to spread if ignored, sometimes presenting as a scaly lesion or ulceration [95]. Melanoma, albeit less common, is the most fatal type of skin cancer, representing around 1% of cases and capable of rapid dissemination; it is typically recognized by changes in an existing mole, adhering to the ABCDE rule [84]. Rare skin cancers include Merkel cell carcinoma (MCC), a rapidly proliferating tumour primarily affecting the elderly or immunocompromised individuals [2], Kaposi sarcoma (KS), frequently seen in immunocompromised patients and associated with human herpesvirus 8, presenting as red or purple lesions [105], dermatofibrosarcoma protuberans (DFSP), a slowly growing tumour resembling a scar [50] and sebaceous carcinoma, an aggressive malignancy of the sebaceous glands, typically found on the eyelids [22]. These mutations, despite differences in incidence and severity, require swift detection and targeted treatment to improve patient outcomes. Additional skin lesions, including Pigmented Bowen's Disease (an early type of squamous cell carcinoma) [61], dermato fibromas, and benign formations such as Pigmented Benign Keratoses [14], vascular lesions [27], and nevi (moles) [103], are generally non-malignant. However, certain benign lesions may mimic cancers or undergo changes, underscoring the importance of ongoing surveillance and dermatological assessments. Risk factors for skin cancer encompass ultraviolet (UV) exposure, fair skin type, and genetic susceptibility. Recent evaluations emphasize that preventive strategies, including sun protection, avoidance of tanning beds, and routine skin examinations, are essential for decreasing skin cancer rates and enhancing early detection. Fig. 1 delineates the classifications of skin cancers.

Consequently, early diagnosis is the pivotal element in the management of skin cancer [89]. Prompt identification is crucial for improving patient outcomes, since it significantly increases survival rates, especially for melanoma [29]. Studies indicate that regular dermatologist-led skin examinations promote the early identification and treatment of skin cancers, thereby reducing overall morbidity [66]. Medical practitioners frequently employ the biopsy technique for the diagnosis of skin cancer. This process entails acquiring a specimen from a suspicious skin lesion for medical analysis to ascertain its oncogenic properties. This procedure is arduous, protracted, and exacting. Dermoscopy enhances the precision of melanoma diagnosis; yet, precisely recognizing certain lesions, especially early melanomas lacking distinguishing dermoscopic characteristics, continues to pose difficulties [20]. Dermoscopy effectively identifies skin cancer; nevertheless, it is inadequate for detecting featureless melanoma, necessitating significant enhancements in accuracy to optimize patient survival rates. Interobserver variability among healthcare practitioners reduces diagnostic accuracy, as differing levels of experience may lead to varied interpretations of the same lesions [16]. Moreover, restricted availability to dermatologists in certain regions impedes prompt diagnoses, highlighting the necessity for improved access to specialized treatment.

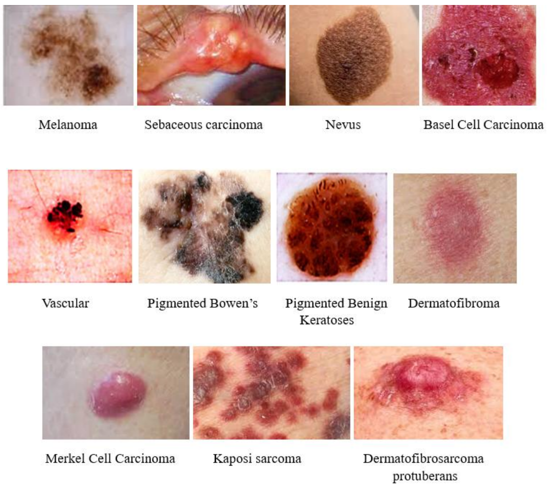

Fig. 1. Samples of different types of skin cancer [97]

The limitations of dermoscopy and the need to enhance the diagnostic accuracy of skin cancer have significantly strengthened the rationale for advancing computer-aided detection methods in skin cancer diagnosis [56]. Deep learning (DL) has emerged as a powerful tool in skin cancer diagnosis, primarily because it can recognize intricate patterns in large datasets that traditional methods may fail to notice [25]. DL models can significantly well perform experienced dermatologists in the accurate diagnosis of skin lesions, making them a vital resource in resource-poor environments where specialists are scarce [34]. Moreover, DL models can continuously improve their performance with additional data exposure, enhancing diagnostic accuracy and enabling earlier detection of skin cancers [96]. Computer-based technology provides a direct, economical, and rapid identification of skin cancer symptoms. Subsequently, additional requirements arose, including hair removal and the reconstruction of pictures processed following a pre-processing step. The Gaussian, mean, and median filters, together with speckle noise filters, are the most commonly employed pre-processing techniques.

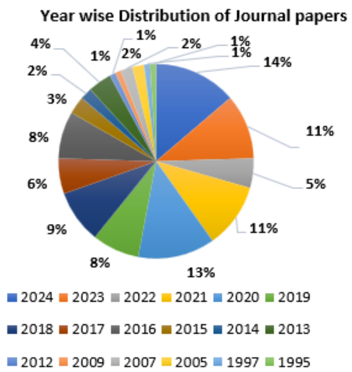

Fig. 2. Year-wise distribution of journal papers used in the literature survey on automated skin cancer diagnosis using deep learning

This survey paper is structured as such. Section 1 offers a short overview of skin cancer diagnostics, while Section 2 clarifies the deep learning architectures utilized and their associated research. Section 3 encompasses the dermatological datasets employed for melanoma identification, whereas Section 4 analyses the various training methodologies implemented in deep learning techniques. Section 5 outlines the performance evaluation measures for skin cancer classification, as well as the challenges and limitations. Section 6 concludes the survey.

1. Deep learning-based skin cancer classification

The systematic investigation provided a comprehensive analysis of the advanced architectures employed in skin cancer categorization. The examined architectures can be broadly categorized into several types, including Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory Networks, Inception Networks, Residual Networks, Dense Networks, MobileNet, and ShuffleNet. This section provides a thorough evaluation of various designs, their applications, and performance analysis in skin cancer classification. Fig. 2 depicts the annual distribution of the 113 journal articles examined in this systematic review, offering an extensive overview of recent progress in automated skin cancer diagnosis utilizing deep learning techniques.

1.1. Convolutional neural networks

Machine learning (ML) algorithms for image interpretation have progressed significantly. Methods such as decision tree learning, clustering, support vector machines (SVMs), K-nearest neighbours (K-NNs), restricted Boltzmann machines (RBMs), and random forests are prevalent machine learning techniques. Nonetheless, these algorithms necessitate discriminative features for optimal performance. Recognizing these characteristics presents a considerable challenge, especially in contexts requiring visual understanding, and remains an area of active investigation. To mitigate this issue, autonomous intelligent systems for picture interpretation and feature extraction have been developed. CNNs have demonstrated outstanding efficacy in interpreting medical images. CNNs employ convolutional filters to learn and extract features from images, effectively capturing spatial hierarchies to analyse grid-like data such as images [91, 98]. CNNs frequently match or exceed human radiologists' performance in cancer identification and segmentation [58]. By analysing extensive labelled datasets, CNNs markedly improve diagnostic precision, rendering them essential in contemporary healthcare [25].

Deep neural networks, especially CNNs, have essential applications such as picture categorization, recognition, and analysis [90]. CNNs integrate fundamental elements such as curves and edges to construct intricate attributes, such as forms and corners, rendering them efficient for both global and local data interpretation [65]. The architecture of CNNs often includes backpropagation, learning algorithms, and regularization techniques. A CNN has hidden layers, which include convolutional, nonlinear pooling, and fully connected layers [59]. Convolutional layers utilize filters to extract features, succeeded by pooling layers that diminish the size of feature maps. The comprehensive interconnected layers integrate the obtained features to generate predictions. This hierarchical structure enables CNNs to effectively analyse and assess images. Unlike traditional neural networks, CNNs employ sparse connections and weight sharing, making them particularly efficient for image processing in digital photography [5]. Fig. 3 illustrates the architecture of a CNN, highlighting the interplay between convolutional, pooling, and fully connected layers. This section lists many recent publications in this category. Majtner et al. [69] utilized CNN for skin cancer diagnosis, leveraging the ISIC dataset and attaining 86% precision and 99.9% specificity with a KNN classifier, surpassing neural networks via unique feature extraction. Nasr-Esfahani et al. [76] devised a CNN for skin cancer diagnosis, with 81% accuracy and 80% specificity utilizing 170 non-dermoscopic images, which were expanded to 6,120 through pre-processing approaches. Fu'adah et al. [26] developed a CNN-based method for the detection of cutaneous and benign tumours, achieving an accuracy of 97.49%. Utilizing the enriched ISIC dataset, the CNN model employing the Adam optimizer achieved an accuracy of 99%, facilitating accurate skin cancer diagnosis by physicians.

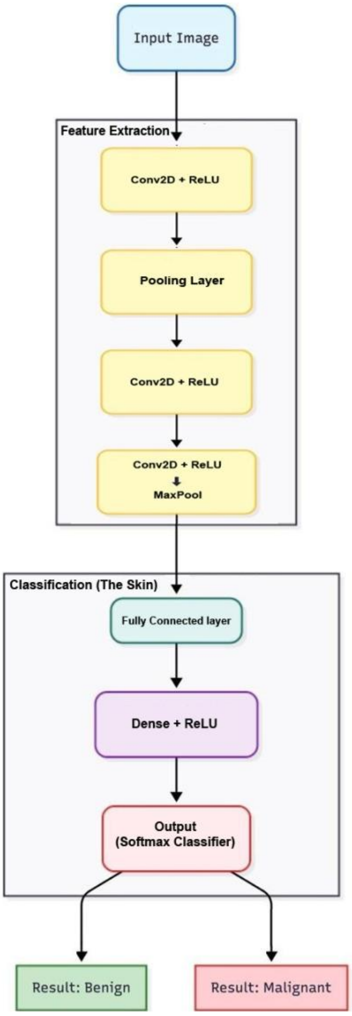

Fig. 3. Schematic representation of a basic CNN architecture

In Fig. 3, the pre-processed dermoscopic image is passed through successive convolutional and ReLU layers to extract low- to high-level skin lesion features. Pooling layers reduce spatial dimensions while preserving salient information. The resulting feature maps are flattened and forwarded to a fully connected layer for learned representation. Finally, a Softmax classifier predicts the lesion category, enabling accurate discrimination between benign and malignant skin conditions.

Hasan et al. [35] proposed a CNN-based approach for automated skin cancer detection, achieving 89.5% overall accuracy and 93.7% training accuracy. This method extracts features from skin cells affected by cancer, establishing a benchmark for skin cancer detection using publicly available data. Gong and Xiao [31] presented a CNN-NLP approach for skin lesion classification, achieving 99.35% accuracy and 83.93% test accuracy. The model employs dense and convolutional layers, while natural language processing enhances patient accessibility and engagement through a chatbot. Kalouche [51] employed VGG-16, a pre-trained convolutional neural network, to classify lesion images, achieving 78% accuracy for melanoma. The optimized model achieved 86.67% accuracy in distinguishing normal skin from lesions, demonstrating effective skin cancer diagnosis. Moturi et al. [74] proposed a deep learning method for skin cancer diagnosis via a customized convolutional neural network, achieving 95% accuracy on the HAM10000 dataset. MobileNetV2 achieved 85% accuracy, and a web application was developed for easy lesion classification. Gupta et al. [32] examined progress in melanoma diagnosis by DL methodologies, emphasizing CNN, DNN, RNN, and transfer learning. They observed restricted clinical applicability and dataset availability, with the ISIC 2020 dataset being the most extensive, albeit still constrained, for melanoma classification. Nasiri et al. [75] introduced DePicT Melanoma Deep-CLASS, a case-based reasoning methodology employing a 16-layer CNN for the classification of skin lesions. The method improved melanoma classification accuracy via recursive training, using the ISIC Archive dataset for image analysis.

1.2. Recurrent neural networks

Recurrent Neural Networks (RNNs) have demonstrated efficacy in skin cancer diagnosis by analysing sequential data, including dermoscopic image sequences and patient histories, thereby enhancing diagnostic precision. Recurrent Neural Networks (RNNs) can facilitate the identification of melanoma and other cutaneous cancers by using temporal dependencies. CNNs and RNNs augment intricate medical imaging through the extraction of features, leading to enhanced categorization and segmentation of dermatological conditions [38]. These hybrids proved highly effective at delineating lesion boundaries over time, assisting dermatologists in the early detection of cancer [67]. Esteva et al. [25] demonstrated that deep neural networks can achieve dermatologist-level accuracy in skin cancer classification, indicating potential for integrating RNNs and CNNs in healthcare diagnostics.

Attia et al. [7] introduced a hybrid CNN-RNN methodology for skin melanoma segmentation, achieving an accuracy of 0.98 and a Jaccard index of 0.93 on the ISBI 2016 dataset. This approach is the most notable advancement in computer-aided melanoma detection to date, demonstrating its clinical relevance and potential. and Divya [21] proposed a melanoma detection methodology that integrates pre-processing, feature extraction, segmentation, and classification. Their methodology achieved 8.06% improvement in accuracy and 15.1% in precision over current approaches, with promise for better segmentation and classification in the diagnosis of skin cancer.

1.3. Long short-term memory networks

Long Short-Term Memory (LSTM) networks are a specific type of recurrent neural network (RNN) intended to process sequential input while alleviating the vanishing gradient problem typically associated with standard RNNs [41]. LSTMs utilize memory cells and gating techniques to detect dependencies across extended sequences, rendering them especially effective in time series forecasting, natural language processing, and medical diagnostics. An LSTM comprises three gates for each memory cell: the input gate, forget gate, and output gate, which regulate the flow of information by selectively retaining or discarding data based on its significance within an order [12]. Results of investigations into the application of LSTM networks to skin cancer detection have been promising, with improved performance metrics, indicating that they are suitable for this task. Recent work by Imran et al. [45] has integrated LSTM models with other DL methodologies, demonstrating significant improvements in diagnostic metrics. A research study combined LSTMs and convolutional networks to extract features from dermoscopic images and achieved an accuracy of 93.50%, specificity of 92%, and sensitivity of 93%. An alternative methodology employing LSTM-based techniques has achieved precision of 97.4%, recall of 93.8%, and an F1-score of approximately 94%, underscoring the model's efficacy in distinguishing benign from malignant nodules, as reported by Gururaj et al. [33]. Gangadevi et al. [28] proposed a novel approach that combines the Intuitive U-Net with LSTM for the identification of skin lesions and melanoma, achieving melanoma accuracy of 98.2% and lesion accuracy of 91.5%, exceeding the state of the art.

1.4. Inception networks

Inception Networks are deep convolutional neural networks that use multiple parallel branches with different filter sizes to effectively capture a wide range of visual data. This architecture allows for greater depth and width without significantly increasing computational cost, thereby improving image classification accuracy. Some of the recent efforts in this direction are as follows. Inception V3, a deep convolutional neural network [92], has achieved outstanding performance in skin cancer classification. It achieved accuracies of 84.39% to 95.4% on the ISIC and HAM10000 datasets, indicating strong diagnostic potential for skin cancer using dermoscopic images. Bazgir et al. [9] stated that the optimized InceptionNet obtained an accuracy of 84.39% with the Adam optimizer and 85.94% with Nadam. The specificity and sensitivity ratings generally fluctuated between 92% to 98%, indicating the model's high reliability in identifying the malignant lesions.

DeVries and Ramachandran [18] created a multi-scale CNN utilizing Inception V3, optimizing it on both coarse-scale and fine-scale lesion pictures for the classification of skin cancer. This method utilized lesion appearance and textual characteristics to distinguish skin lesions, hence improving diagnostic precision. Alanazi [4] proposed a CNN system based on Inception v3 for melanoma diagnosis, employing transfer learning and trained on ISIC datasets. The model achieved 98.96% precision, surpassing contemporary methodologies and demonstrating improved prediction accuracy and reliability in skin cancer diagnosis. Sahu et al. [81] introduced a DL methodology for melanoma diagnosis with the Inception V3 model augmented with a bespoke top classification layer. The model trained on the Skin Cancer Detection dataset achieves a classification accuracy of 96.00%. The work illustrates the efficacy of CNNs in skin cancer diagnosis by automating feature extraction, surpassing traditional methods.

1.5. Residual networks

Residual Networks (ResNets) [37] are renowned for mitigating the "vanishing gradient" problem in deep neural networks by employing residual connections that enable effective layer bypassing. This architecture enables ResNets to maintain good accuracy in very deep networks without the performance degradation often associated with increased network depth. ResNet models, particularly ResNet50 and ResNet101, have demonstrated exceptional effectiveness across many image classification tasks, especially in medical imaging, thanks to their ability to learn hierarchical features from complex images. Recent endeavours in this domain are briefed in this section.

Hermosilla et al. [39] demonstrated that ResNet50 achieved 95.2% accuracy in melanoma classification on the HAM10000 dataset, whereas models employing GAN-based augmentation with ResNet architectures showed improved precision and recall. Dhibar's [19] study used ResNet101 and deep auto-encoder techniques, attaining 95.80% accuracy in skin cancer detection. The model exhibited strong competence by utilizing ResNet101 for extraction and an autoencoder for dimensionality reduction to improve image quality and diagnostic accuracy. Mehra et al. [71] developed a deep convolutional neural network for melanoma detection. A fully convolutional residual network (FCRN) including 16 residual blocks improved segmentation efficacy. The proposed classification method included an SVM and a softmax classifier. The precision of melanoma classification was 85.5% with segmentation and 82.8% without it. Elshahawy et al. [24] suggested a melanoma detection model that integrates YOLOv5 with ResNet50, utilizing the HAM10000 dataset for training. The model achieved 99.0% precision, 98.6% recall, and 99.5% accuracy, surpassing current models in terms of inference speed and diagnostic precision. Budhiman et al. [10] assessed ResNet topologies (ResNet-50, 40, 25, 10, and 7) for melanoma classification with the ISIC 2018 dataset. ResNet-50 attained the highest performance, with 83% validation accuracy and an F1 score of 0.4. Mendonca et al. [72] introduced a DL methodology employing ResNet-50 for skin cancer classification, attaining an accuracy of 84.87% on the HAM10000 dataset. ResNet-50 outperformed VGG16 and other CNN models, demonstrating strong predictive performance for early skin cancer diagnosis. Acosta et al. [49] introduced the eVida M6 model, which integrates Mask RCNN with ResNet152 for the diagnosis of skin cancer. The model achieved 90.4% accuracy and 92.5% specificity, surpassing ISIC 2017 models by 3.66% in classifying benign and malignant tumours.

1.6. Dense networks

Dense network topologies, such as DenseNet-121 and DenseNet-169, have demonstrated significant efficacy in skin cancer detection tasks. These models excel by establishing broad linkages among layers, hence increasing feature propagation and minimizing redundant learning. Yin et al. [102] employed DenseNet-169 on the ISIC 2019 and PAD-UFES-20 datasets, attaining an accuracy of 95.4%, precision of 88.8%, recall of 89%, F1-score of 90%, and a ROC-AUC of 96%. Hermosilla et al. [39] employed DenseNet-201 on the HAM10000 dataset, achieving 95.2% accuracy, 96.8% precision, and an AUC-ROC of 0.98. DenseNet-201 exhibited a robust capacity to recognize and distinguish between benign and malignant skin lesions. Girdhar et al. [30] developed deep learning models for melanoma detection, tailoring ResNet, DenseNet, Inception, and VGG for the HAM10000 dataset. The DenseNet-II model achieved 97.35% accuracy and 95.7% F1-score, outperforming other models after 20 epochs of training. Kaushik et al. [53] employed DenseNet-121 for melanoma diagnosis utilizing the ISIC 2019 dataset, achieving an accuracy of 90%. The model demonstrated adaptability to various lesion types, thereby indicating its efficacy in melanoma detection and its potential for real-time applications and collaborative assessment.

1.7. MobileNet

MobileNet is an efficient deep learning architecture designed for mobile and embedded vision applications. It decreases computing complexity by the utilization of depth-wise separable convolutions while maintaining accuracy, rendering it appropriate for resource-limited devices. MobileNet achieved a balance between performance and efficiency for applications such as image classification [82]. Howard et al. [42] employed MobileNetV2 on the HAM10000 dataset, attaining 92.7% accuracy, 90.2% precision, and 95.6% ROC-AUC. MobileNetV2's efficiency and capacity to identify intricate patterns render it suitable for real-time skin cancer diagnosis in mobile dermatological applications. Indraswari et al. [46] introduced a melanoma classification method utilizing MobileNetV2, attaining a peak accuracy of 85% across multiple datasets. This efficient method utilizes transfer learning and a customized head model. It represents an equilibrium between efficiency and precision, making it suitable for mobile melanoma detection. Hartanto and Wibowo [36] created an Android application for skin cancer diagnosis with Faster R-CNN and MobileNet v2. The system attained remarkable accuracy, with MobileNet v2 demonstrating efficacy on smartphones, thereby facilitating early cancer diagnosis through mobile devices and point-of-care diagnostics. Zakariah et al. [104] introduced a dual-model methodology for skin cancer detection, integrating MixNets with MobileNet-based transfer learning. The algorithm achieved 99.58% accuracy on the ISIC dataset, effectively distinguishing between benign and malignant tumours, indicating the possibility for high-precision diagnostics.

1.8. ShuffleNet

ShuffleNet is an efficient architecture designed for mobile devices. It integrates point-wise group convolutions with channel shuffling to reduce computational expenses and enhance efficiency. ShuffleNet achieves superior performance in image classification tasks by improving speed and accuracy, making it ideally suited for real-time applications. Recent advancements in this domain encompass the following: Zhang et al. [106] utilized ShuffleNet on the ISIC dataset, achieving an accuracy of 91.3%, a precision of 89.5%, and a ROC-AUC of 94.2%.

The economic structure of ShuffleNet, characterized by channel shuffling and group convolutions, renders the network suitable for mobile applications in skin cancer detection that necessitate rapid processing and efficiency. Devaraj and Ravi [17] draw inspiration from a multi-branch architecture inspired by ShuffleNet for skin cancer classification. This model utilizes cross-channel information exchange and global feature aggregation to provide superior feature extraction and high classification accuracy on the ISIC2019 and ISIC2020 datasets. Baig et al. [8] presented a streamlined variant of Dermo utilizing a lightweight convolutional neural network model that employs channel-wise focus for the diagnosis of multiclass pigmented skin disorders.

1.9. Contemporary works

This section highlights recent contemporary works (CW) that demonstrate significant progress in skin cancer detection, with advanced machine learning and deep learning models that enhance diagnostic accuracy, robustness, and clinical applicability. Kumar et al. [60] presented a comprehensive approach to skin cancer detection and classification using machine learning and deep neural networks, achieving 98.56% accuracy on a dataset of 10,015 dermatoscopic images. Their model can detect and classify seven specific types of skin cancer, including vascular lesions, dermatofibroma, basal cell carcinoma, melanocytic nevi, melanoma, benign keratosis-like lesions, and actinic keratoses. Jayaseeli et al. [48] developed and implemented two CNN architectures, such as YOLO v7 and an in-house algorithm, for the classification of three common types of skin cancer lesions, using 2,792 training samples and applying data augmentation techniques to improve model performance. Zhang et al. [107] demonstrated that unsupervised learning methods can achieve strong performance in skin lesion classification using enhanced imaging techniques, reporting test accuracies of 87.77% on the ISIC2019 dataset and 90.5% on the HAM10000 dataset. Jayaseeli et al. [48] proposed an intelligent framework combining Squeeze-Excitation-DenseNet with metaheuristic-driven ensemble deep learning models, reaching high accuracies of 98.38% and 98.17% on benchmark datasets. Similarly, Abdulredah et al. [1] introduced SkinWiseNet (SWNet), a deep convolutional neural network that achieved 99.86% accuracy and 99.95% F1 score, effectively addressing skin tone and hair-related biases by fusing features from diverse datasets.

2. Recent Deep Learning architectures

Recent breakthroughs in deep learning have led to the development of efficient architectures, including Transformers, Encoder-Decoder models, attention-based models, and Generative Adversarial Networks. These architectures have achieved exemplary performance across numerous medical imaging tasks, including skin cancer diagnosis. Some are summarized in this section.

Himel et al. [40] employed Vision Transformer for the categorization of skin lesions, with an accuracy of 96.15% on the HAM10000 dataset. Pre-processing procedures and lesion segmentation with the Segment Anything Model improved the model's robustness. The self-attention mechanism of ViT adeptly captures spatial interdependencies, demonstrating its promise as a reliable diagnostic tool for dermatologists. Google's ViT patch-32 showed improved performance with a low false-negative rate. Yang et al. [101] introduced an innovative skin cancer categorisation technique via a transformer-based methodology. The approach encompasses class rebalancing, image pre-processing, and token processing via a transformer encoder. Transfer learning was utilized using ImageNet and subsequently fine-tuned on HAM10000. The method achieved 94.1% accuracy, exceeding that of the state-of-the-art IRv2 and baseline models on the Edinburgh DERMOFIT dataset, thereby demonstrating its effectiveness in improving skin cancer diagnosis. Khan et al. [55] introduced SkinViT, an innovative architecture for the classification of Melanoma and Nonmelanoma skin malignancies. SkinViT integrates an outlooker block, transformer block, and MLP head block to capture fine-level and global features. Evaluated on three datasets, SkinViT achieved high classification accuracies (0.910, 0.891, and 0.861), outperforming state-of-the-art models and demonstrating its potential to aid dermatologists in early skin cancer diagnosis. Mohn et al. [73] employed Vision Transformers, Swin Transformers, and DinoV2 for skin disease classification. DinoV2 achieved 96.48% test accuracy and 0.9727 F1-Score, outperforming benchmarks by 10%. Robustness was validated on HAM10000 and Dermnet datasets. Explainable AI frameworks (GradCAM, SHAP) identified disease-associated image regions, aiding dermatologists in early diagnosis and treatment.

Ijaz et al. [43] proposed lightweight encoder-decoder (ED) architectures, MobileUNet and EfficientUNet, leveraging MobileNetV2 and EfficientNetB0 blocks. Evaluated on ISIC 2017 and 2018 datasets, these models achieved up to 12% performance improvement over the baseline UNet. Intended for embedded platforms, they offer low power consumption, excellent performance, and minimal memory requirements while maintaining accuracy and the Jaccard index. Karimi et al. [52] proposed the Dual-Encoder U-Net (DEU-Net) to address challenges in automated lesion segmentation. DEU-Net combines the convolutional and transformer encoders to extract local and global contextual information. Tested on four skin lesion datasets (ISIC 2016, 2017, 2018, and PH2), DEU-Net achieved high Dice coefficients (92.90%–95.65%) and accuracy (97.58%), outperforming modern methods and demonstrating its efficacy in skin cancer diagnosis. Shahin et al. [85] proposed an encoder-decoder (ED) model with pyramid pooling modules for skin melanoma segmentation. Inspired by PSP-Net, this approach aggregates global context and compensates for spatial information loss. Evaluated on ISIC 2018, the model achieved a Jaccard index of 0.837, outperforming U-Net and demonstrating potential for clinical implementation, although further validation and efficiency analysis are recommended. Wibowo et al. [100] proposed an enhanced skin lesion segmentation method using MobileNetV3-UNet with a bidirectional ConvLSTM layer and separable blocks. The approach incorporated data augmentation and stochastic weight averaging. Evaluated on ISIC-2017, ISIC-2018, and PH2 datasets, the method achieved high Dice coefficients (87.74%–95.18%) and accuracy (93.81%–98.70%), outperforming state-of-the-art methods.

Qin et al. [77] introduced a style-based GAN for skin lesion classification to improve classification performance. Upon evaluation using ISIC 2018, the images generated by the GAN enhanced classification metrics, attaining 95.2% accuracy, 83.2% sensitivity, and 96.6% average precision. This technique demonstrated substantial improvements over a CNN model, demonstrating the efficacy of GAN-generated images in augmenting classification performance for skin cancer diagnosis. Rahman et al. [78] introduced an innovative framework for skin cancer diagnosis that tackles issues of limited datasets, data imbalance, and overfitting. It employs GANs to produce supplementary training images, Bi-LSTM to alleviate memory limitations, and AVOA for optimal feature selection. Upon evaluation on the ISIC dataset, the technique achieved 98.5% accuracy, markedly improving early melanoma detection and demonstrating its potential for precise skin cancer diagnosis. Sedigh et al. [83] introduced a convolutional neural network for skin cancer diagnosis, tackling the issue of inadequate annotated data. The model was trained on 97 ISIC pictures and attained an accuracy of 53%. To augment performance, a GAN produced synthetic images, elevating accuracy to 71% when incorporated into the dataset. This method illustrates the efficacy of GANs in enhancing CNN-based models for skin cancer detection.

Finally, Wang et al. [99] proposed a two-stage framework for melanoma detection, addressing challenges of high similarity between benign and malignant lesions and class imbalance.

Evaluated on ISIC2020, the approach achieved 98.43% accuracy, 98.63% AUC, and 99.01% sensitivity, surpassing existing methods. This framework demonstrates potential in enhancing melanoma detection, improving efficiency and accuracy over traditional visual inspection methods.

The comparison presented in Table 1 clarifies the benefits and limitations of several deep learning-based skin cancer classification methods. The findings indicate that CNN-based methods exhibit enhanced performance, facilitating future studies in skin cancer diagnosis.

A comparative analysis of leading deep learning architectures for skin lesion classification reveals clear performance trends. A comparative analysis of leading deep learning architectures for skin lesion classification reveals clear performance trends. Conventional CNN models demonstrate moderate effectiveness, achieving an average accuracy of 88.14%, specificity of 90.6%, and precision of 84.62%, reflecting strong but architecture-limited feature extraction. DenseNet-based models show notable improvements, with an average accuracy of 94.25%, F1-score of 92.85%, and recall of 89%, attributed to dense feature propagation and reduced redundancy. ResNet variants perform similarly well, reaching an average accuracy of 95.23% due to enhanced residual learning. Transformer-based methods achieve competitive results, with an average accuracy of 94.25%, thanks to global attention mechanisms well-suited to complex dermoscopic patterns. Inception architectures deliver an average accuracy of 90.97%, offering efficient multi-scale feature extraction.

Table 1. Comparative analysis of deep learning-based skin cancer classification techniques used in the proposed work

Authors	Architecture	Datasets	Methodology	Results
Majtner et al. [69]	CNN with AlexNet	ISIC 2017 Dataset	Pre-processing: grayscale, AlexNet for feature extraction, LDA for reduction,	Precision: 86%, Specificity: 99.9%
Nasr-Esfahani et al. [76]	CNN	170 dermoscopic images, augmented to 6,120	Pre-processing: CNN with input, Convolutional pooling, and FC layers.	Accuracy: 81%, Specificity: 80%
Yunendah Nur Fu'adah et al. [26]	CNN	ISIC 2017 dataset	Pre-processing & and augmentation, optimized using Adam optimizer.	Accuracy: 99%
Hasan et al. [35]	CNN	Public dataset	Feature extraction and classification of dermoscopic cells.	Accuracy: 93.7%, Recall: 84% Precision: 83.25%
Gong and Xiao [31]	CNN-NLP	Skin lesion dataset	Four convolutional layers, NLP-enhanced patient interaction.	Accuracy: 83.93%
Kalouche [51]	VGG-16	Derm Net	Fine-tuned VGG-16 with boundary detection and classification.	Accuracy: 78%
Moturi et al. [74]	Customized CNN, MobileNetV2	HAM10000 Dataset	Classification of dermoscopic tumours, a web application for image uploads.	MobileNetV2 Accuracy: 85%, Customized CNN Accuracy: 95%
Attia et al. [7]	Hybrid CNN-RNN	ISBI 2016 dataset	Segmentation and classification using a hybrid CNN-RNN.	Accuracy: 98%, Jaccard Index: 93%
Imran et al. [45]	LSTM + CNN	Dermoscopic image dataset	Combined sequential data modeling with convolutional feature extraction.	Accuracy: 93.50%, Specificity: 92%, Sensitivity: 93%
Gangadevi et al. [28]	Intuitive U-Net + LSTM	Custom dataset	Temporal modelling with the U-Net's feature extraction.	Melanoma Accuracy: 98.2%, Lesion Accuracy: 91.5%
Bazgir et al. [9]	Inception Network	HAM10000	Transfer learning, Adam and Nadam optimizers for classification improvement.	Accuracy: 85.94%, Specificity: 92-98%, Sensitivity: 92-98%
Sahu et al. [81]	Inception V3	ISIC 2018	Custom top classification layer, automated feature extraction.	Accuracy: 96%
Hermosilla et al. [39]	ResNet50	HAM10000 Dataset	GAN-based augmentation, hierarchical feature extraction for classification.	Accuracy: 95.2%, Enhanced precision and recall rate.
Dhibar [19]	ResNet101 + DAE	ISIC 2018 Dataset	Deep feature extraction with dimensionality reduction,	Accuracy: 95.80%, F1-Score: 0.953, ROC-AUC: 0.97
Elshahawy et al. [24]	YOLOv5 + ResNet50	HAM10000 Dataset	Feature map integration for real-time melanoma detection.	Accuracy: 99.5%, Precision: 99%, Recall: 98.6%, MAP: 98.7%
Jojoa et al. [49]	Mask RCNN + ResNet152	ISIC 2017 Dataset	Two-phase detection: bounding box delineation and lesion categorization.	Accuracy: 90.4%, Specificity: 92.5%
Yin et al. [102]	DenseNet-169	ISIC 2019, PAD-UFES-20	Dense interconnections facilitate feature propagation and reduce the need for duplicate learning.	Accuracy: 95.4%, Precision: 88.8%, Recall: 89%, F1-score: 90%, ROC-AUC: 96%
Girdhar, et al. [30]	DenseNet-II	HAM10000	Customized model trained over 20 epochs for melanoma classification.	Accuracy: 97.35%, F1-score: 95.7%
Kaushik et al. [53]	DenseNet-121	ISIC 2019 Dataset	Deep CNN with optimized layers for real-time lesion detection.	Accuracy: 90%
Himel et al. [40]	Vision Transformer (ViT)	HAM10000	Pre-processing (normalization, augmentation), SAM for lesion segmentation.	Accuracy: 96.15%, Dice: 98.14%
Yang et al. [101]	Transformer-based	HAM10000, DERMOFIT	Pre-processing (patch splitting, tokenization), Transformer encoder.	Accuracy: 94.1%
Khan & Khan [55]	SkinViT	ISIC2019, Combined datasets	Transformer blocks and feature extraction with an Outlooker and an MLP head.	Accuracy: 91.09%
Mohn et al. [73]	Vision Transformer (DinoV2)	HAM10000, Dermnet	Transfer learning (ImageNet1k), GradCAM, SHAP for explainable AI.	Accuracy: 96.48%, F1-Score: 0.9727.
Ijaz et al. [43]	MobileUNet, EfficientUNet	ISIC2017, ISIC2018	Lightweight ED architectures, optimized for embedded platforms.	Accuracy: ISIC2017: +12% over baseline, ISIC2018: Jaccard and Dice indices improved.
Karimi et al. [52]	Dual-Encoder U-Net (DEU-Net)	ISIC2016–2018, PH2	Combines convolutional and transformer encoders.	Accuracy: 97.58%
Wibowo et al. [100]	MobileNetV3-UNet	ISIC2017, ISIC2018, PH2	Bidirectional ConvLSTM layer, separable blocks, data augmentation	Accuracy: ISIC2017: 93.81%, ISIC2018: 94.79%, PH2: 98.70%
Qin et al. [77]	Style-Based GAN	ISIC2018	GAN for synthetic image generation, evaluated on classification metrics	Accuracy: 95.2%, Sensitivity: 83.2%, Specificity: 74.3%,
Rahman et al. [78]	GAN, Bi-LSTM, AVOA	ISIC	GAN for data generation, Bi-LSTM for memory constraints, and AVOA for feature selection	Accuracy: 98.5%
Sedigh et al. [83]	CNN	ISIC	GAN for synthetic image generation to expand the dataset	Accuracy: Without GAN: 53%, With GAN: 71%
Wang et al. [99]	Two-Stage Framework	ISIC2020	Address dataset imbalance and melanoma using deep learning	Accuracy: 98.43%, Sensitivity: 99.01%

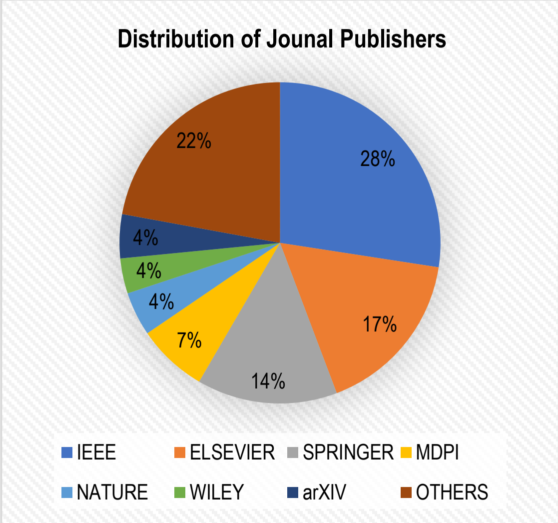

Fig. 4. Distribution of journal publishers of the reviewed papers on automated skin cancer diagnosis using deep learning

Fig. 4 presents a pie diagram illustrating the distribution of journal publishers, including IEEE, Elsevier, Springer, MDPI, and others. Notably, IEEE leads with the most papers, followed by Elsevier, Springer, MDPI, and others, indicating the prominent sources of research in this domain. Also, Fig. 5 presents a comprehensive overview of the deep learning architectures employed in the survey. The prominent architectures utilized in this domain include Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory Networks (LSTM), Inception Networks (IN), Residual Networks (RN), Dense Networks (DN), MobileNet (MN), ShuffleNet (SN), Generative Adversarial Networks (GAN), Vision Transformer (VIT), and Encoder-Decoder (ED). Fig. 5 highlights the diversity of the architectures being explored for automated skin cancer diagnosis, underscoring the need for a systematic evaluation of their performance and effectiveness [57].

Dermatological imaging requires highly specialized feature extraction because skin lesions exhibit subtle chromatic shifts, multi-scale textural gradients, and clinically critical morphological patterns absent in generic image datasets. Accurate melanoma detection depends on capturing pigment networks, streaks, globules, vascular cues, border irregularities, and lesion evolution, which are often missed by conventional extractors. Furthermore, dermatoscopic images suffer from illumination variability, device artifacts, and skin-tone diversity, necessitating domain-adaptive pre-processing. Thus, effective architectures must employ multi-resolution encoding, high-fidelity texture modelling, and clinically informed feature priors to achieve robust, diagnostic-grade lesion discrimination far beyond standard image classification frameworks.

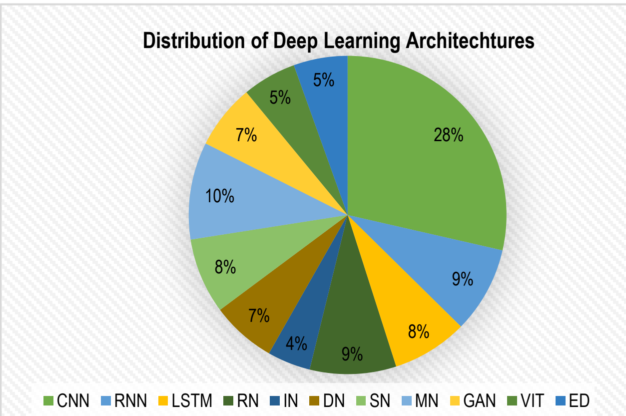

Fig. 5. Distribution of the deep learning architectures used in automated skin cancer diagnosis using deep learning

3. Dermatological datasets for melanoma diagnosis

Effective computer-assisted skin cancer diagnosis necessitates high-quality dermoscopic images for evaluation. Nonetheless, current datasets are constrained, diverse, and biased in favour of melanocytic lesions. The insufficiency of data inhibits the training of artificial neural networks for skin lesion categorization, underscoring the need for diverse and comprehensive dermatological datasets [87]. This section provides genuine datasets for assessing prospective skin cancer detection techniques. Table 2 delineates the principal elements of these databases. A study on skin cancer detection employs each dataset for image classification, segmentation, and diagnosis.

Table 2. Overview of Publicly Available Dermatological Datasets for Skin Lesion Diagnosis and Classification

Sl. No.	Dataset / Subclass Types	Size (Nos)	Weight (%)
1	**DATASET- ISIC 2024 [47]**	**4,01,059**	**100**
a	Nevus	2,00,529	50
b	Melanoma	80,212	20
c	Basal cell carcinoma	40,106	10
d	Actinic keratosis	24,064	6
e	Vascular lesions	20,053	5
f	Dermatofibroma	20.053	5
g	Benign keratosis	16,042	4
2	**DATASET- MIDAS [13]**	**3,830**	**100**
a	Nevus	2,259	59
b	Melanoma	958	25
c	Basal cell carcinoma	306	8
d	Actinic keratosis	192	5
e	Benign keratosis	115	3
3	**DATASET- HAM10000 [97]**	**10,015**	**100**
a	Nevus	6,009	60
b	Melanoma	2,604	26
c	Basal cell carcinoma	901	9
d	Actinic keratosis	501	5
4	**DATASET- PH2 [72, 73]**	**200**	**100**
a	PH2	60	30
b	Basal Cell Carcinoma (BCC)	50	25
c	Squamous Cell Carcinoma (SCC)	40	20
d	Actinic Keratosis	26	13
e	Vascular Lesions	10	5
f	Merkel Cell Carcinoma	10	5
g	Dermatofibroma	4	2
5	**DATASET- ISIC Archive [15]**	**25,331**	**100**
a	Benign Nevus	18,491	73
b	Melanoma	4,560	18
c	Basal Cell Carcinoma (BCC)	1,013	4
d	Actinic Keratosis	507	2
e	Seborrheic Keratosis	507	2
f	Dermatofibroma	253	1
6	**DATASET- DermQuest [79]**	**22,082**	**100**
a	Basal Cell Carcinoma (BCC)	9,936	45
b	Melanoma	5,079	23
c	Squamous Cell Carcinoma (SCC)	3,975	18
d	Actinic Keratosis	1,546	7
e	Cutaneous Lymphoma	1104	5
f	Merkel Cell Carcinoma	442	2
7	**DATASET- DermIS [86]**	**6,588**	**100**
a	Basal Cell Carcinoma (BCC)	2,569	39
b	Melanoma	1,252	19
c	Squamous Cell Carcinoma (SCC)	988	15
d	Actinic Keratosis	791	12
e	Cutaneous Lymphoma	593	9
f	Merkel Cell Carcinoma	395	6
8	**DATASET- AtlasDerm [64]**	**1,024**	**100**
a	Basal Cell Carcinoma	296	29
b	Actinic Keratosis	246	24
c	Squamous Cell Carcinoma	205	20
d	Melanoma	154	15
e	Cutaneous Lymphoma	51	5
f	Others (e.g., benign lesions)	72	7
9	**DATASET- Dermnet [94]**	**23,000**	**100**
a	Basal Cell Carcinoma (BCC)	11960	52
b	Squamous Cell Carcinoma (SCC)	5060	22
c	Melanoma	2990	13
d	Actinic Keratosis	1610	7
e	Cutaneous Lymphoma	920	4
f	Others	460	2

4. Training strategies in deep learning-based skin cancer classification

Training regimens are essential for enhancing deep learning models, particularly in applications such as skin cancer classification where data may be scarce or unbalanced. These strategies improve generalization, model robustness, and convergence rates, making them indispensable in medical imaging and classification applications. Data Augmentation artificially enlarges the training dataset by implementing adjustments (e.g., rotations, flips, and zooms) to existing images, hence assisting models in generalizing across various data variances. Data augmentation is essential in medical imaging to enhance the model's ability to accommodate variations in skin tone and lesion shape [93]. Transfer learning initializes model weights with those derived from pre-trained networks, usually learned on large datasets like ImageNet. This approach improves performance and reduces training time for medical images, where labelled data is scarce [3]. Fine-tuning entails the targeted training of specific layers within a pre-trained model to enhance its performance on a new dataset. In medical applications, the last layers are usually altered to improve feature extraction for skin cancer classification [91]. Regularization Techniques like as dropout and L2 regularization mitigate overfitting by reducing the model's complexity or incorporating noise. These methodologies improve generalization, especially advantageous in constrained medical datasets [44]. Batch Normalization normalizes the input of each mini-batch, hence reducing internal covariate shifts. It stabilizes training, promoting expedited convergence and enhanced performance in deep networks [1]. Rate of Learning Scheduling adjusts the model's learning rate over time, promoting consistent convergence throughout the final stages of training. Cyclical learning rate techniques enhance convergence by modulating the rate within specified intervals [68].

5. Performance parameters, challenges and limitations

Performance metrics for skin cancer detection often encompass accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC-ROC), which evaluate the efficacy of classification algorithms [11]. These metrics assess the model's efficacy in identifying malignant lesions while reducing false positives and false negatives, as demonstrated in the Confusion Matrix presented in Table 3. A confusion matrix assesses the effectiveness of a classification model. It compares the actual labels with the expected labels, facilitating the evaluation of the model's effectiveness. True Positive (TP) refers to successfully identified positive cases, False Positive (FP) suggests erroneously identified positive cases, False Negative (FN) indicates incorrectly identified negative cases, and True Negative (TN) implies correctly identified negative cases. This section summarizes all the different variables.

Table 3. Layout of the Confusion Matrix for Classification in Deep Learning Algorithms

	Predictive: Positive	Predictive: Negative
Actual: Positive	True Positive (TP)	False Negative (FN)
Actual: Negative	False Positive (FP)	True Negative (TN)

Accuracy: Accuracy quantifies the proportion of correct predictions relative to the total predictions generated by the model. It provides a fundamental performance metric, computed using equation (1).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (1)$$

Precision and Recall: Precision is vital in clinical environments to reduce false positives and avoid misclassifying benign cases as malignant. Simultaneously, recall (or sensitivity) is emphasised as crucial for the effective detection of malignant instances, calculated using Equations (2) and (3), respectively.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

F1-Score: This metric is emphasized for its equitable methodology, particularly with imbalanced datasets, guaranteeing the preservation of both high precision and recall. The F1-Score is computed using equation (4).

$$\text{F1-Score} = 2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \quad (4)$$

ROC-AUC: The Receiver Operating Characteristic – Area Under Curve is an essential indicator for evaluating a model's ability to distinguish between malignant and benign cases, regardless of a specific threshold, enabling a thorough performance assessment. It plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold levels.

Sensitivity: The proportion of genuine positive cases correctly identified by the model. Increased sensitivity is crucial in skin cancer diagnosis to ensure the accurate identification of potential malignant cases. Sensitivity is ascertained utilizing equation (5).

$$\text{Sensitivity} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)+False Negatives (FN)}} \quad (5)$$

Specificity: Specificity evaluates the model's effectiveness at identifying genuine negatives (benign cases) by calculating the ratio of true negatives to the total of true negatives and false positives. Specificity is calculated using equation (6).

$$\text{Specificity} = \frac{\text{True Negative (TN)}}{\text{True Positives (TP)+False Negatives (FN)}} \quad (6)$$

5.1. Challenges, limitations and emerging trends

The diagnosis of skin cancer by DL encounters obstacles due to class imbalance that favours benign lesions and the scarcity of high-quality annotated datasets, which diminishes the model's effectiveness in identifying uncommon malignant tumours and its practical applicability [25].

Deep learning models are susceptible to overfitting, particularly when trained on limited datasets, demonstrating proficiency during training, but are unable to generalise to novel data. Overfitting undermines the model's dependability on real-world datasets. Siddique et al. [88] investigated strategies to mitigate this problem, encompassing data augmentation and regularization techniques, to enhance model robustness and generalizability. In the categorization of skin cancer, a lack of transparency may erode trust. Interpretability is crucial for physicians to understand model judgments. Linardatos et al. [63] evaluated interpretability methods, including Grad-CAM and SHAP, to improve transparency and dependability in critical applications such as skin cancer diagnosis.

Despite significant advances in research, it is important to note that image-based AI diagnosis serves only as advisory support, with definitive clinical decisions made by physicians based on comprehensive assessments. Nevertheless, the methodological advancements in AI architectures, feature extraction, and performance evaluation offer significant technical value for researchers and developers

Hybrid models integrating machine learning techniques and various data sources are emerging for skin cancer classification. The integration of DL with conventional approaches and Explainable AI [70] techniques boosts classification effectiveness and transparency [80]. The seamless integration of clinical workflows with teledermatology platforms enables prompt, reliable diagnoses, thereby increasing access to dermatological care and promoting healthcare equity. These methodologies possess the capacity to transform the diagnosis and treatment of skin cancer, especially in marginalized regions. Subsequent investigations must concentrate on these nascent patterns.

6. Conclusion

This survey examines current developments in DL for skin cancer diagnosis. This paper emphasizes the promise of DL techniques in skin cancer classification through architectural developments, comparative analysis, and dermatological datasets. Nonetheless, obstacles and constraints, including dataset variability, class imbalance, and overfitting, persist. Emerging concepts such as transfer learning, ensemble methods, and multimodal analysis hold promise for tackling these difficulties. Future research should focus on developing more reliable, precise, and clinically relevant methods for diagnosing skin cancer. To support clinical integration, AI systems should be validated using diverse, real-world dermatological datasets and integrated into routine workflows through clinician-friendly interfaces. Additionally, collaborative decision-support frameworks should be implemented to ensure that AI outputs complement, rather than replace, expert clinical judgment.

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