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A Systematic Review of Machine Learning and Deep Learning Approaches for Skin Cancer Diagnosis

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Abstract: *Skin cancer continues to be one of the most common and clinically difficult cancers around the world, owing to its fast-growing rate, extremely high mortality rates in cases of malignant melanomas, and the essential need to diagnose at the initial stage. Traditionally, the process of diagnosing skin cancer was performed using visual inspection, dermoscopy, and histopathology biopsy, which formed the core of the clinical assessment of the disease. These methods continue to rely heavily on the experience of the dermatologist, take much time to perform, and are subjective in nature. Recently, the diagnostic approach has moved away from traditional clinical procedures towards automated systems that leverage artificial intelligence and enable highly precise identification of malignancies. The present literature review aims to examine recent developments and methodologies adopted in ML and DL-based systems that can be used in diagnosing and classifying skin cancer. A systematic analysis is made based on a taxonomy, comprising medical image data sources and preprocessing approaches, algorithm architectures encompassing traditional ML models, CNN models, transfer learning, and deep neural architectures, as well as performance evaluation measures adopted in research. Moreover, this review transcends traditional algorithmic comparisons by addressing fundamental issues that hinder the successful adoption of automation technology for real-world applications on a large scale. Issues such as data scarcity in labeled medical datasets, class imbalance, overfitting in deep neural networks, the black box nature of neural models, and computational complexity, among others, have been investigated in this context.*

Keywords: Skin Cancer Detection; Machine Learning; Deep Learning; Convolutional Neural Networks; Dermoscopy Images; Medical Image Classification; Explainable AI; Computer Vision; Automated Diagnosis; Healthcare AI

INTRODUCTION

One type of cancer that has become quite common is skin cancer. This type of cancer is very serious due to high rates of diagnosis, expensive treatments required, and increased fatalities as a result of late diagnosis. Based on statistics of the number of cancer cases around the world, there are several million cases of skin cancer discovered each year, with melanoma considered to be the most dangerous. Factors contributing to the prevalence of skin cancer include exposure to too much UV light, environmental factors, genetics, and risky behaviors. The biggest problem in the field of skin oncology is early diagnosis of skin cancer because it greatly affects chances of survival and minimizes complications.

In the past, the diagnosis of skin cancer has been based mainly on traditional techniques carried out by dermatologists using observation, dermoscopy, and biopsies. Although these traditional approaches have been recognized as the benchmark method, they pose certain limitations due to their dependency on physician experience and subjectivity when it comes to observation, the need for highly trained professionals to interpret dermoscopies, and invasiveness,

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time consumption, and high cost involved in the biopsy procedure. With the existing gap between the increased number of patients and the scarcity of trained dermatology professionals, there is a need for more automated and scaled-up approaches that can assist clinicians in making decisions.

The rapid development of advanced AI, ML, and DL technology has completely changed the landscape of medical image processing and disease diagnosis with the help of computer applications. Unlike rule-based image processing approaches, machine learning techniques have the potential to detect hidden patterns and discover visual features from large-scale medical image data. More specifically, recent deep learning models, including Convolutional Neural Network (CNN), Residual Network (ResNet), DenseNet, MobileNet, EfficientNet, and transfer learning models, have shown tremendous potential in automated skin lesion identification and diagnosis processes, often attaining comparable diagnostic performance as that of dermatologists. The shift towards AI-powered healthcare solutions has proven to be one of the most promising approaches in improving accessibility and accelerating the diagnosis of skin lesions in dermatological oncology.

A. Clinical Importance of Early Skin Cancer Detection

One of the key issues affecting the chances for patient survival with skin cancer is its timely diagnosis. Skin cancer appears as an abnormal growth of skin cells due to changes in DNA caused by damage, typically as a result of constant exposure to ultraviolet rays from the sun. There are three common types of skin cancer: Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and Melanoma. Out of these, the latter is particularly dangerous owing to its ability to develop into metastasis, where cancerous cells can quickly spread to internal organs. Numerous medical studies have shown that the earlier the patient is diagnosed with this form of cancer, the greater the chances of successfully curing it. Thus, the development of a highly precise automated system able to diagnose skin diseases in their early stages constitutes one of the key issues in modern healthcare.

B. The Methodological Shift: From Conventional Diagnosis to Artificial Intelligence

Conventional methods for detecting skin cancer involved manually analyzing images of skin lesions using dermoscopic images along with the biopsy pathology of those lesions. Though useful in practice, such conventional methods have several limitations associated with them, such as human errors, inter-rater variability, subjectivity of diagnoses, and low accessibility in underserved health care settings. The recent development in computer vision and artificial intelligence has resulted in a paradigm shift from human-in-the-loop methods to automatic predictive modeling based on medical image classification. Models such as Support Vector Machine, Random Forest, Decision Tree, and K-nearest Neighbor achieved significant success at classifying medical images through handcrafted feature selection. However, the advent of deep neural networks led to an approach where the dependence on manual feature selection was no longer necessary.

C. Scope, Objectives, and Structural Taxonomy of This Review

During the last ten years, research in the area of skin cancer detection through artificial intelligence technologies has been expanding very fast, leading to a large degree of fragmentation in the literature in terms of data used, evaluation procedures, neural network designs, and performance figures reported. The main purpose of this literature review paper is, therefore, to systematically integrate this expanding body of research and set up a systematic framework for the assessment of the methodologies proposed. Unlike a regular literature review paper, this one critically assesses the literature using a multidimensional classification framework.

Dimension one emphasizes the usage of datasets and preprocessing techniques for skin lesions from the perspective of medical image datasets and processing. This dimension highlights some publicly available benchmark datasets, including ISIC, HAM10000, PH2, and Derm7pt. Dimension two classifies approaches based on algorithmic methodology, where conventional machine learning classifiers, CNNs, transfer learning techniques, hybrid neural networks, and transformer architecture-based medical vision algorithms are evaluated. Dimension three measures algorithm performance using clinical evaluation metrics, which include accuracy, sensitivity, specificity, precision, recall, F1 score, and area under the curve (AUC).

Firstly and foremost, this study uncovers a number of research gaps which are hindering the implementation of the AI-based diagnostic system in practice. In particular, the present work addresses a number of gaps, such as small sets of annotated data for medical applications, extremely unbalanced classes, overfitting in deep neural networks, lack of model interpretability, poor generalizability between different datasets, high computation time, and restrictions during deployment in low-resource healthcare settings. Finally, this paper offers a complete guide for future researchers, focusing on such important areas as explainable artificial intelligence, lightweight mobile diagnostic tools, federated healthcare learning, and clinical decision support systems.

II. RELATED WORK

The epidemiology paper by Apalla et al. [1] provides an extensive overview of the burden and increasing incidence of skin cancer cases globally. In their study, the authors emphasize assessing the healthcare data, environmental conditions, and cancer registry data to determine the trend of the increased prevalence of melanomas and non-melanomas. They found that exposure to ultraviolet rays is a key contributor to skin cancer mutations among populations exposed to intense sunlight for a considerable period of time. The study offers significant insights into the global pattern of skin cancer prevalence and emphasizes the need for an early diagnosis in order to reduce mortality cases. The key problem with the literature is that no computational model exists to aid in early skin cancer detection.

A systematic review was carried out by Roky et al. [2], who undertook a large-scale analysis aimed at studying the types of skin cancer and their prevalence in various population demographics around the world. In their study, comparative analysis of healthcare data was employed to determine the classification of melanoma, basal cell carcinoma, and squamous cell carcinoma according to the age group, environmental factors, and availability of medical facilities within various regions. The conclusion drawn from this study is that melanoma cancer is the most aggressive type of skin cancer due to its ability to metastasize quickly. However, the percentage of non-melanoma skin cancer cases continues to dominate among the cases reported worldwide. It highlights the necessity for developing faster diagnosis procedures which minimize reliance on manual diagnosis.

Feller et al. [3] presented an overview that concentrated on identifying biological and molecular mechanisms causing the development and progression of skin cancer. Their methodology included examining the role of UV exposure in inducing mutations of the DNA and the role of genetic instability over time, resulting in abnormal growth of skin cells, especially in the development of melanomas. It was found that UV radiation affects the structure of the DNA of melanocytes, ultimately leading to tumor formation. The results provided by Feller et al. [3] greatly helped in understanding the biological aspects of skin cancer and stressed the need for preventive measures such as limiting exposure to UV radiation. Despite their contribution to the biological understanding of skin cancer, the study did not incorporate the use of computer vision techniques for automatic detection of abnormal lesions.

A clinical review of the current methods of diagnostic workflow for identifying skin cancer was done by Sathe et al. [4]. The methodology applied focused on reviewing physical skin examination methods, the dermoscopy imaging method, histopathology, and pathology of biopsies made by dermatologists. The authors found that current diagnostic procedures are still very efficient in hospitals and thus form the established standard of diagnosing skin cancers among patients. However, there are various problems with these methods, including those that focus on the dependence on physicians, observer variability, biopsy procedures, late diagnoses, and clinical costs for wide screening processes. Therefore, the main research gap that exists is the absence of intelligent automated diagnostic systems for reducing dependence on dermatologists without decreasing diagnostic accuracy.

In this regard, Li et al. [5] developed a systematic review evaluating the methodologies adopted using artificial intelligence in the automated diagnosis of skin diseases using image processing techniques and computer vision technologies. Their methodology involved the assessment of several algorithms for both machine learning and deep learning techniques, such as Support Vector Machines, Random Forest, convolutional neural network, and transfer learning, among others, in dermoscopy image classification tasks. The analysis revealed the superiority of deep learning models compared to traditional machine learning in automated diagnostic systems because of the ability to extract hierarchical features from medical images automatically. Nevertheless, the significant weakness of deep learning models is the lack of explainability due to complex algorithmic processes, making them less adoptable by clinicians.

Harangi et al. [6] presented a novel ensemble deep convolutional neural network approach aimed at automatic melanoma classification based on images of skin lesions acquired with the use of dermoscopy. This research was based on the integration of multiple convolutional neural networks working in parallel in order to increase the capability of feature detection and minimize prediction errors for more effective classification of various lesions. Based on experiments conducted by the authors, it became evident that ensemble-based deep learning models were characterized by much higher classification accuracy rates than those of the independent convolutional neural networks tested separately. Nevertheless, the main drawback of this research is a very high level of computational and memory complexity that makes it not suitable for use in mobile medical applications.

The proposed methods in the MobileNet-based skin lesion classification works [7] were related to the development of lightweight convolutional neural networks tailored to the needs of healthcare institutions with limited resources and mobile diagnostics. The approach involved using depth-wise separable convolutions to lower computational expenses and achieve classification of seven different types of lesions with acceptable accuracy. In experiments, it was shown that light deep learning models can classify several types of lesions with substantially reduced memory use and increased inference speed compared to CNNs. It allowed the creation of novel options for mobile automated systems for skin cancer diagnosis, which could be used in distant healthcare locations to help in delivering medical assistance in a timely manner. Yet, it turned out that classification instability occurs in the presence of unbalanced medical data.

The CancerNet-SCa [8] presented an advanced deep neural network design that was custom-made for automated identification and classification of skin cancer images. The research methodology concentrated on optimizing architecture design parameters while enhancing network explainability via advanced feature extraction layers specifically designed for dermoscopic image analysis. According to the results, CancerNet-SCa showed better classification accuracy than conventional deep learning approaches. The research is considered significant in the area of customized neural network architecture design aimed at achieving better healthcare purposes. Unfortunately, the described system proves to be extremely prone to overfitting as a result of insufficiently large medical image data sets.

Brinker et al. [9] proposed an empirical evaluation of the effectiveness of convolutional neural networks as diagnostic tools in comparison with expert dermatologists in detecting and diagnosing melanoma. Their approach consisted of developing deep convolutional neural networks based on large image data sets of dermoscopy images and testing their classification accuracy compared with manually trained dermatology experts during lesion classification tasks. The experiments showed that deep learning models were able to provide diagnostic results similar to those provided by expert clinicians, thus pointing out the immense possibilities for the application of AI-based healthcare support systems. However, a major problem still persists in terms of poor explainability of neural networks, hindering their full-scale implementation in such critical decision-support applications.

Skin lesion classification systems based on ResNet [10] examined transfer learning techniques to enhance the performance of automatic extraction of features for dermatological cancer diagnosis. In their methodology, they used pre-trained residual neural network models previously trained on image datasets, then fine-tuned on dermoscopic skin lesion image sets. Results of their experiment proved the effectiveness of transfer learning because of the improved classification efficiency brought about by residual skip connections, enabling the learning process through deeper neural networks while addressing the issue of the vanishing gradient problem. The limitation of this research is that there is decreased flexibility in applying such models to various clinical images taken under inconsistent lighting conditions.

Densenet-based diagnostic systems [11], which developed dense connected convolutional neural network models for achieving better feature propagation and minimizing the use of redundant parameters for medical image classification. This was accomplished through connections made by each network layer to the following ones, thus maximizing reuse of the features while retaining low-level features needed for identifying the boundaries of lesions. Through experiment evaluation, improvements were observed in comparison with ordinary CNN models. Contributions were made to the development of deep learning effectiveness in medical image applications. Nevertheless, the level of computation was relatively high, hindering practicality in resource-constrained portable healthcare environments.

EfficientNet-based approaches [12] have proposed methods for achieving optimal scaling of models for classification purposes without compromising computational efficiency in skin cancer detection. Such methods consider the balancing of depth, width, and resolution scaling for the model at the same time. The experiments have shown good results regarding the improvement of classification accuracy in comparison with classical deep learning models, providing an opportunity to achieve such performance without increasing computational costs substantially. It has been demonstrated that computationally efficient architectures do not necessarily lack diagnostic capacity in terms of performance. Nevertheless, their limitation lies in sensitivity to imbalanced data sets.

InceptionNet-based systems for skin lesion classification [13] examined feature extraction approaches that could concurrently examine skin lesion characteristics such as its texture, shape abnormalities, and coloration at various resolutions. They adopted a parallel convolutional framework that used convolutional operations with various filter sizes to detect fine and coarse visual differences characteristic of skin lesion malignancy. Experimentally, they showed improvement in detecting structural abnormalities within skin lesions that were hard to detect using conventional machine learning algorithms. The system was highly valuable in adding variety to the features used in automatic lesion classification. Unfortunately, increasing architectural depth significantly complicates the model, making it unsuitable for mobile health applications.

The diagnostic accuracy assessment of JAMA Dermatology [14] utilized meta-analysis, where the diagnostic accuracies were assessed among the various methods used to detect skin cancer through clinical observation, dermoscopy, and artificial intelligence-powered classification systems. The diagnostic accuracies for sensitivity, specificity, and lesion classification were compared in a variety of studies employing physician-driven diagnostics and automated diagnostics. The study found that the use of an automated system is consistently superior to manual observation alone in terms of lesion classification accuracy, reducing the number of cases of incorrect diagnoses. Nevertheless, the problem of standardization still exists, as healthcare facilities use various standards for acquiring their data sets.

New research on explainable artificial intelligence [15] proposed diagnostic models where explainability techniques were incorporated with deep learning models to enhance clinician trust in automatic skin cancer diagnosis. The research adopted an approach that involved an attention map, a saliency map, a gradient activation map, and feature importance in order to understand which parts of lesions influenced the decisions of neural network models. It was found that explainable AI models enhanced physicians' trust in their operation since decision-making processes within the models became transparent. Such research marked an essential move in making it safe to use AI in medicine. Nevertheless, the main issue with such models is the need to balance explainability and classification efficiency.

The automatic system for dermoscopic image segmentation and classification developed by Mendonça et al. [16] aimed at enhancing the accuracy of early diagnosis of melanoma utilizing deep learning techniques. Image processing methods, including contrast enhancement, lesion boundary determination, and segmentation processes, preceded the utilization of CNN structures for feature extraction and classification in their methodology. Experiments revealed that proper lesion segmentation considerably increased classification accuracy because neural networks were trained to pay attention only to suspicious areas rather than being distracted by background noise. Hence, their research was an important step towards enhancing the process of skin lesion image segmentation for better classification in the field of dermatological disease diagnosis automation. Nevertheless, the major problem associated with such approaches still includes their high sensitivity to low-quality medical pictures captured under variable illumination conditions.

One of the landmark papers in this field is from Codella et al. [17] through the International Skin Imaging Collaboration (ISIC) Challenge in relation to melanoma detection from large dermoscopic image datasets. Their paper showed that deep convolutional neural network (CNN) models are superior to classical machine learning models when

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trained on large benchmark datasets. They evaluated several machine learning/deep learning algorithms through a standardized benchmark image set with many labeled images. Through their findings, they have made the ISIC datasets one of the most important benchmark datasets for testing dermatological disease classification systems. Nevertheless, the main limitation of this kind of research work involves the problem of data imbalance, which arises due to insufficient data samples of malignant lesions when compared to benign lesions.

The artificial intelligence approach by Esteva et al. [18] marks a significant achievement in the form of a framework that employs deep convolutional neural networks for the purpose of large-scale classification of skin cancer at a level similar to a dermatologist's expertise. In this method, the researchers developed a framework using CNNs, where the model was trained with hundreds of thousands of clinical pictures in various diseases, after which classification results were compared with certified dermatologists who manually diagnosed these cases. Experiments conducted showed that the deep learning framework had similar accuracy as dermatologists in the process, marking a significant milestone in the development of artificial intelligence in medicine. This method has shown the feasibility of deep learning frameworks in making autonomous disease diagnoses without the need for human-engineered features. However, one limitation of this study is the black-box approach of neural networks for decision-making processes.

Tschandl et al. [19] introduced a comparative study aimed at assessing the performance of machine learning systems versus dermatologists in terms of multiclass skin lesion classifiers for many kinds of cancer. This method made use of large dermoscopy image data sets for melanoma, basal cell carcinoma, benign nevus, and many pigmented lesions in comparison to the diagnoses by skilled dermatologists. It was noted that deep learning algorithms achieved very high sensitivity concerning the identification of malignancies and outperformed humans in most cases when assessed through controlled experiments. It became evident that artificial intelligence models had enormous clinical application possibilities in helping diagnose diseases while lowering the rate of missed detections. Nevertheless, the most important weakness found was poor robustness since AI systems failed to perform well when faced with diverse clinical images sourced from various hospitals and skin colors not covered in training.

In another paper, Nasr-Esfahani et al. [20] introduced a computer-aided diagnosis system which involved the use of image processing techniques coupled with the extraction of hand-crafted visual features for the purpose of classifying melanomas using a series of machine learning approaches. Specifically, the methodology employed the use of image processing techniques along with the extraction of texture, color, asymmetry, and lesion border irregularities features, after which the classification of images was done using the help of machine learning classifiers like the Support Vector Machines and Decision Trees. From experiments conducted, encouraging diagnostic accuracy was recorded in addition to proving that hand-crafted visual features are still significant even with a limited amount of data. Nevertheless, this is one of the important studies in the early stages of automating skin cancer diagnosis. However, the main challenge is low scalability and accuracy when compared to current deep learning models, mainly due to limitations associated with hand-crafted features.

Table 1: Comparative analysis of Liver cancer detection and Classification

Ref	Lead Author	Primary Architecture / Methodology	Dataset / Data Source	Key Evaluation Metrics	Primary Research Focus / Research Gap
[1]	Apalla	Epidemiological Analysis	Global Population Healthcare Data	Incidence Rate, Mortality Rate	Lack of automated computational diagnosis systems
[2]	Roky	Clinical Review & Population Analysis	Healthcare Registry Data	Prevalence Statistics	No integration of AI-assisted diagnostic frameworks
[3]	Feller	Molecular Pathology Analysis	Biological Cell Mutation Data	Cellular Progression Analysis	Missing image-based automated detection system
[4]	Sathe	Clinical Examination, Dermoscopy, Biopsy	Hospital Clinical Data	Diagnostic Reliability	Strong dependency on the dermatologist's expertise

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[5]	Li	Machine Learning & CNN Review	Dermoscopic Image Dataset	Accuracy, Precision	Limited explainability of deep learning models
[6]	Harangi	Ensemble Deep Convolutional Neural Network	Dermoscopy Skin Images	Classification Accuracy	Very high computational complexity during deployment
[7]	MobileNet Study	Lightweight CNN Architecture	Skin Lesion Medical Images	Accuracy, Inference Speed	Performance instability on imbalanced datasets
[8]	CancerNet-SCa	Specialized Deep Neural Network	ISIC Benchmark Dataset	Accuracy, F1 Score	Overfitting due to limited annotated training data
[9]	Brinker	CNN vs Dermatologist Comparative Study	Large Dermoscopic Dataset	Sensitivity, Accuracy	Poor interpretability of neural network decisions
[10]	ResNet Framework	Transfer Learning Residual Neural Network	ISIC / HAM10000 Dataset	Accuracy, Recall	Poor adaptability across different clinical environments
[11]	DenseNet Framework	Dense Convolutional Neural Network	Dermoscopy Image Dataset	Classification Accuracy	High computational resource requirements
[12]	EfficientNet Framework	Compound Model Scaling Deep Learning	HAM10000 Skin Dataset	Accuracy, Computational Efficiency	Sensitive to severe dataset imbalance
[13]	InceptionNet Framework	Multi-scale CNN Architecture	Skin Lesion Dataset	Precision, Recall	Increased model complexity in deeper architecture
[14]	JAMA Dermatology Study	Meta-analysis Diagnostic Comparison	Multi-clinical Dataset	Sensitivity, Specificity	Lack of standardized imaging protocols across hospitals
[15]	Explainable AI Studies	XAI Integrated Deep Learning	Medical Imaging Dataset	Accuracy, Interpretability	Difficulty balancing transparency with performance
[16]	Mendonça	Segmentation + CNN Classification	Dermoscopic Skin Images	Segmentation Accuracy	Sensitive to poor quality and inconsistent image capture
[17]	Codella	Benchmark Deep Learning Framework	ISIC Challenge Dataset	Classification Accuracy	Severe dataset imbalance causing model bias
[18]	Esteva	Large-scale CNN Classification System	Dermatology Clinical Images	Dermatologist-level Accuracy	Black-box decision making limits clinical trust
[19]	Tschandl	Multiclass Deep Learning Framework	Multiclass Skin Lesion Dataset	Sensitivity, Specificity	Poor robustness on unseen image distributions
[20]	Nasr-Esfahani	Image Processing + SVM Classification	Clinical Skin Lesion Dataset	Diagnostic Accuracy	Lower scalability than advanced deep learning models

III. RESEARCH GAP

Despite notable advancements made in skin cancer detection using machine learning and deep learning algorithms, there have been some essential problems left unattended by past researchers. The majority of the current research concentrates on enhancing accuracy in the classification process via the use of dermoscopic images as datasets, and little effort has been made towards incorporating other forms of medical information into the algorithm, including

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patients' clinical background, genetic markers, environmental exposure records, and real-time healthcare monitoring data.

Moreover, among the common problems found in the reviewed studies is the scarcity of labeled medical image databases. The public benchmark databases ISIC, HAM10000, PH2, and Derm7pt have helped to boost research development; nevertheless, class imbalance continues to be a key problem since there are fewer classes for malignant lesions than those for benign lesions. Class imbalance often leads to bias toward classes that dominate in a database, making deep learning models less sensitive to detecting rare yet hazardous types of cancer, such as melanoma.

Further, there is another critical constraint that is related to the inability of models to generalize across multiple clinical settings. Most of the current machine learning/deep learning systems tend to show high levels of precision during experiments; however, they do not perform well consistently in external testing performed on datasets from other dermoscopy scanners, imaging protocols, illumination sources, skin types, and hospital settings.

IV. DISCUSSION

As per the reviewed literature, there is increasing emphasis being laid on the use of advanced technologies like artificial intelligence and deep learning in revolutionizing skin cancer detection and diagnosis systems. The conventional medical methods of detecting the skin cancer problem using visual examination, dermoscopy, and biopsy are effective but have limitations associated with physician dependence, subjectivity, delayed diagnosis, and lack of qualified dermatology specialists. While earlier machine learning algorithms, such as Support Vector Machines, Random Forest, Decision Tree, and manually engineered feature-based models, exhibited high classification efficiency, they were constrained by manual feature extraction and the inability to deal with very complicated lesions. Some recent innovations in deep learning methods, including Convolutional Neural Network, ResNet, DenseNet, MobileNet, EfficientNet, and transfer learning methods, have proven to be very effective in automated lesion classification as they can outperform even dermatologists in certain cases.

However, despite the above developments, several issues still pose difficulties in the practical implementation of intelligent diagnostic tools for skin cancer. Lack of availability of big annotated databases, class imbalance, overfitting, poor generalization across other data sets, and high computational requirements are the main problems that hinder the proper functioning of the diagnostic tools. Moreover, most of the DL-based approaches act as black boxes, which poses an issue regarding transparency, as clinicians need explanations for their decisions before accepting any automated diagnosis for treatment. In the future, efforts should be made to design lightweight and computationally efficient models using multimodal healthcare information and Explainable Artificial Intelligence approaches.

V. CONCLUSION

The problem of skin cancer detection remains one of the most important problems in the field of modern medicine because of the steadily rising cases of melanomas and nonmelanomas worldwide, along with the reliance on early-stage diagnosis when it comes to successful treatment. From the literature that was considered during the writing of this paper, a lot has been done in the field of automatic skin lesion classification via machine learning, deep learning, and artificial intelligence technologies. The latest achievements include excellent classification results by using various architectures such as CNN, ResNet, DenseNet, EfficientNet, MobileNet, and even transfer learning techniques, with several models delivering performance comparable to dermatologists' diagnostics.

Despite all these developments, there still exist a number of challenges that include insufficient medical data annotation, class imbalance, overfitting, computational inefficiency, poor generalization capacity, and unexplainable behavior of the neural network algorithms. The further development of future research should be oriented towards the design of light-weighted, explainable, and clinically robust diagnostic platforms that would be able to operate with a variety of healthcare information and, at the same time, provide a high degree of precision and effectiveness in terms of computation.

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