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Skin Disease Recognition Based On Deep Learning Algorithms: A Review

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Abstract

The sharp increase in cases of melanoma and other skin cancers worldwide highlights the urgent need for improved diagnostic methods. Because skin lesions vary widely and access to dermatological knowledge is limited in resource-poor areas, traditional methods - which rely on visual inspection and clinical experience - have difficulty identifying diseases accurately. This situation requires innovative approaches to improve accessibility and diagnostic accuracy. To address these issues, this work uses deep learning (DL) and convolutional neural networks (CNNs). This paper is trying to transform skin cancer diagnosis through the use of large databases of dermoscopic images and advanced artificial intelligence algorithms. In order to evaluate the effectiveness of CNNs and DL in identifying skin diseases, we conducted a comprehensive analysis of the literature, focusing on the accuracy of skin cancer type classification. Our approach focused on model architectures, data preparation methods, and performance indicators while examining existing research using AI algorithms to diagnose skin cancer. With the ultimate goal of improving patient outcomes through early detection and accurate classification of skin conditions, this approach not only underscores the great potential of DL and CNN in transcending traditional diagnostic limitations, but it also highlights the continued development of AI-based tools in dermatology.

A. Introduction

Skin cancer has become one of the most common types of cancer worldwide in recent years due to a sharp increase in its incidence. The incidence of melanoma, the deadliest form of skin cancer, is alarmingly high, so this increase is particularly worrying. Enhancing the effectiveness of treatment and increasing patient survival rates requires early detection and accurate classification of skin cancer types. The emergence of artificial intelligence (AI), especially in the form of deep learning (DL) and convolutional neural networks (CNNs), has revolutionized the way skin cancer is detected and classified. This has given hope to those fighting this aggressive disease. Combating skin cancer has become an urgent necessity due to its rapid spread and the major financial and health consequences it causes to individuals. Although sometimes successful, traditional diagnostic techniques often rely too heavily on the training and experience of medical specialists. The diagnosis process is further complicated by differences in appearance between benign moles and malignant tumors, especially in the early stages of skin cancer. This context is the ideal environment for studying advanced automated systems that can use artificial intelligence algorithms to increase the accuracy and effectiveness of skin cancer diagnosis. Even with improvements in skin imaging techniques, accurate interpretation of the complex morphological features of skin lesions remains challenging. Research such as those conducted by [1][2][3]. Highlight how DL and CNN can be used to overcome these limitations. By using advanced AI models and large datasets of dermatoscopy images, this research has shown significant increases in skin cancer classification accuracy. It is worth noting that a model combining reinforcement learning and learning learning was presented by [3][4][5][6], which achieved an accuracy rate of 80% in classifying skin cancer into seven types. This creative method perfectly captures the proposed answer to the problem: combining reinforcement learning and deep learning to create AI-based diagnostic tools that are accurate and capable of continuous improvement through training and retraining procedures. The aim of this review paper is designed to provide a comprehensive assessment of the status of AI applications in skin cancer diagnosis at present [7]. Basic information is covered in the first section, which also emphasizes the need for early detection and the high incidence of skin cancer. Next, we talk about the problem at hand and the AI-based solutions that have been proposed, highlighting the contribution of CNNs and DL to improving diagnostic accuracy [8] [9]. The following sections of the paper are devoted to a comprehensive analysis of the approaches, results and implications of important works in this field. Through a comprehensive analysis of these findings, the study seeks to clarify the effectiveness of AI in skin cancer diagnosis and investigate potential avenues for further investigation and implementation in clinical settings.

The organization of this paper is as follows: Section B,C,D,E and F Background Theoretical, Section G Related Works, and Related Work Summary Table, Section H Discussion, Section I Conclusion.

B. Introduction to Deep Learning and Skin Problems.

A. Overview of Skin Diseases and Diagnostic Difficulties
Millions of people around the world are affected by a wide range of diseases known as skin diseases, which can include benign disorders as well as malignant cancers. These disorders have a complex diagnostic approach based primarily on visual examination and the physician's experience. However, a number of obstacles stand in the way of this traditional method, such as subjectivity of visual assessment and variability in disease presentation, which may lead to inaccurate diagnoses [3][10] and [11] As show in figure 2. Furthermore, these difficulties are exacerbated by the lack of competence in dermatology in low-resource settings, underscoring the need for innovative diagnostic approaches [12] [13]. As show in figure 1.

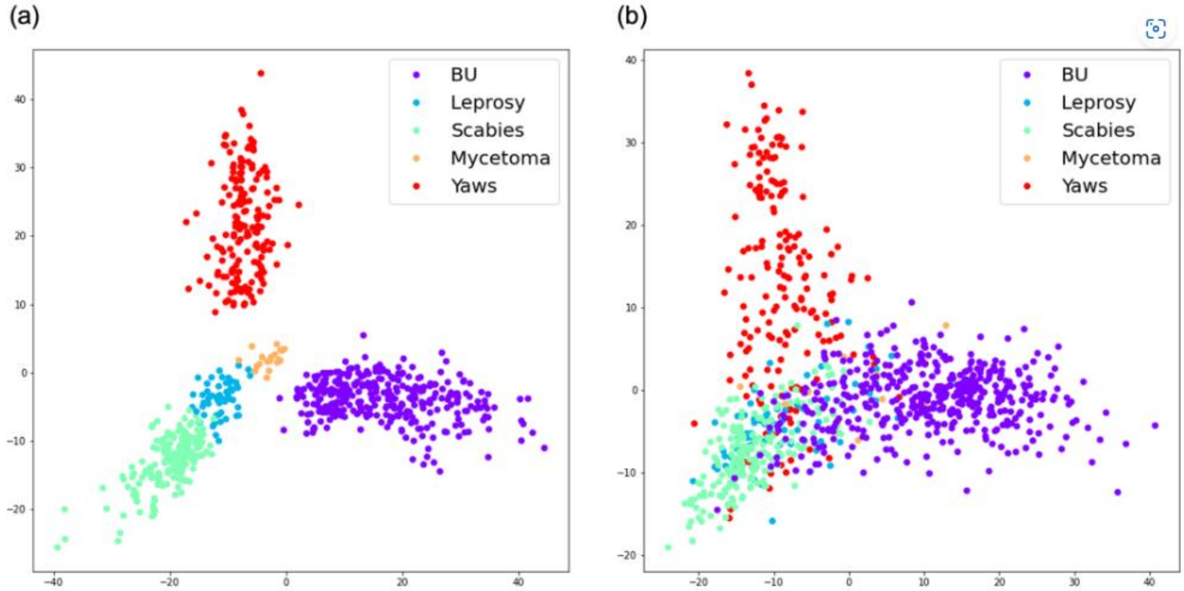

Figure 1. Principal components analysis diagnostic accuracy mapping. (a) Using training samples from five diseases. (b) Test samples from five diseases [12].

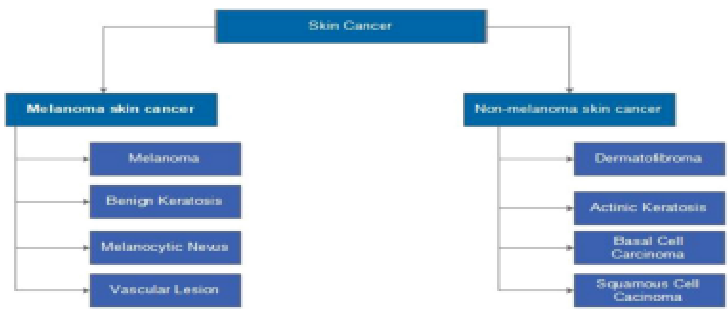

Figure 2. Types of skin cancer, including non-melanoma and melanoma [10].

B. An Overview of Deep Learning for Studying Medical Images
Deep learning (DL), a branch of artificial intelligence (AI) that focuses on algorithms and neural networks that can learn and make intelligent judgments on their own, has become a leading tool for medical image analysis in response to

these diagnostic issues. Precision diagnosis in dermatology has a new path thanks to the remarkable ability of deep learning models, in particular convolutional neural networks (CNNs), to identify patterns and features in medical images that are invisible to the human eye[13][14][15] As show in figure 5. These models use large datasets to learn and improve, which helps them become more efficient in accurately diagnosing a variety of skin disorders [16][17] As show in figure 3 and 4.

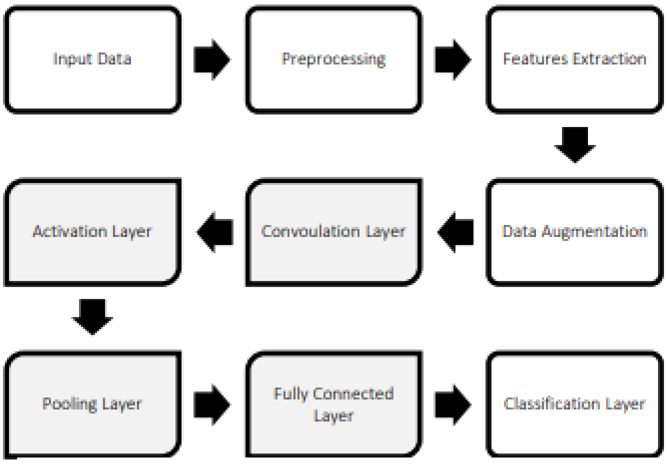

Figure 3. Proposed CNN Architecture [17].

Figure 4. Classifications of skin diseases using information from ISIC [16].

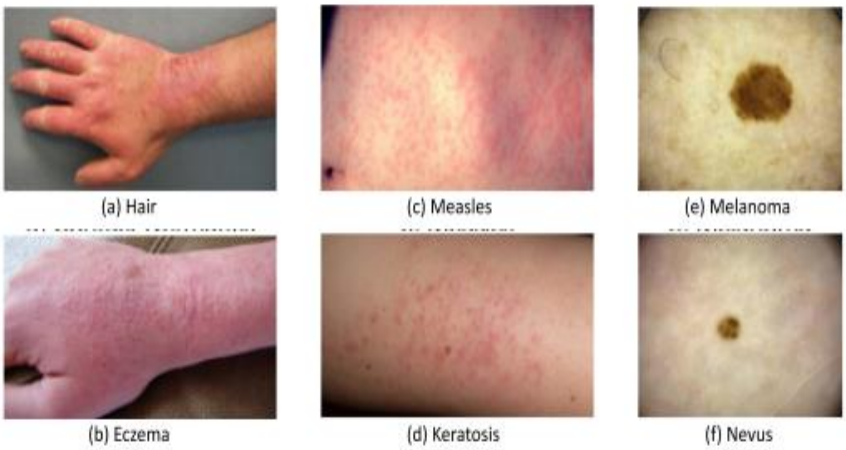

Figure 5. Prevalent skin conditions [15].

C. Automatic Recognition Systems and their Importance

The diagnosis of skin diseases can be completely transformed by automated recognition systems based on DL algorithms, which provide reliable, rapid and consistent identification of diseases. These systems are particularly important for addressing the diagnostic difficulties described previously, providing dermatologists with a second opinion, and allowing non-specialists to make the initial diagnosis. This capacity is essential for increasing access to dermatology care in poor areas, where there are often more skin problems and fewer resources available for health care. [18][19] As show in figure 6. Furthermore, by enabling early identification and treatment, these technologies can significantly enhance patient outcomes. By integrating AI and distance learning into the diagnostic workflow, a new era of accessible, efficient and equitable digital dermatology is being ushered in. This represents a potential step towards reducing worldwide inequalities in the detection and treatment of skin diseases [20][21] As show in figure 7.

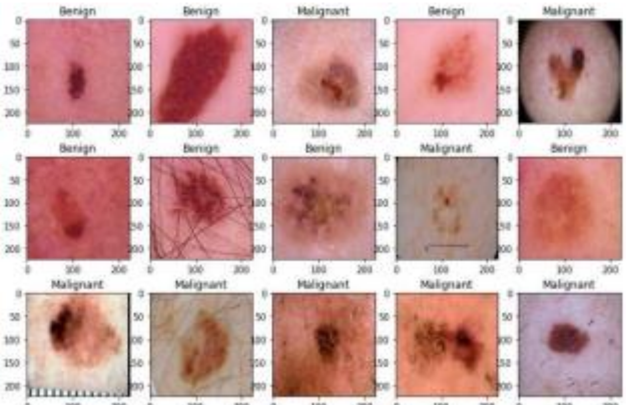

Figure 6. Some images of the dataset [18].

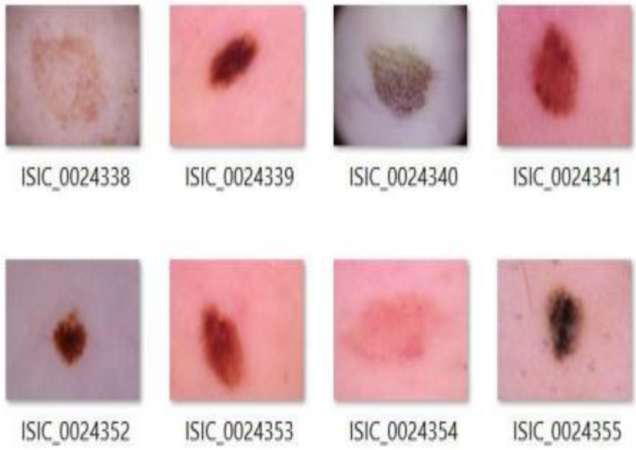

Figure 7. Examples of HAM10000 image types [20].

C.Foundations of Deep learning

A. Neural Network Basics

Deep learning relies on neural networks, which mimic the structure and functions of the human brain to teach robots from data. Neural networks, as Potter (2024) explains, consist of layers of neurons, each designed to identify patterns by modifying connections in response to input data. This method paves the way for solving complex problems across multiple domains by supporting the model's ability to learn from and make predictions from unseen data .As show in figure 8

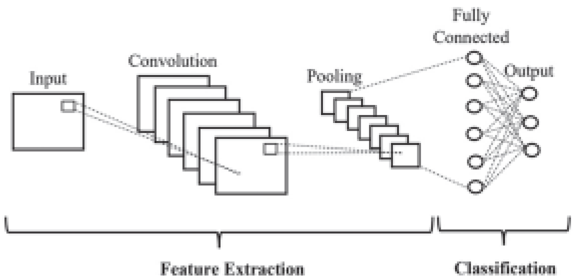

Figure 8. Building convolutional neural networks [3].

B. Convolutional Neural Networks (CNNs)

CNNs are a subclass of deep neural networks that are essential for visual vision analysis. Its distinctive design, which automatically and adaptively learns the spatial hierarchy of features from input images, was highlighted in [14] and [22]. Because of this feature, CNNs are well-suited for tasks that involve recognizing visual patterns in digital images, ranging from simple shapes to complex objects. As show in figure 9

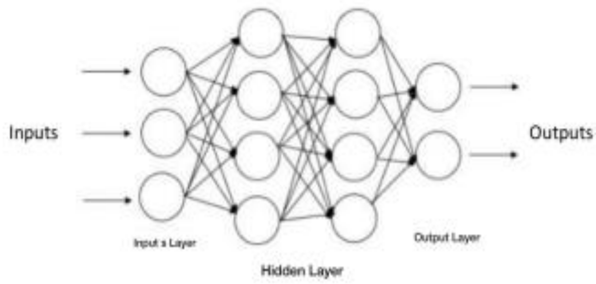

Figure 9. CNN organizational structure [23].

C. Transfer Learning

Applying knowledge from one activity to address related but different problems is known as transfer learning, as described in [24]. This method works particularly well in deep learning, where it can be used to fine-tune models pre-trained on large data sets for specific tasks with less data. This method significantly reduces the time and resources needed to train models from scratch.

D. Deep Learning: Emerging Frontiers In Dermatology Diagnostics

Deep learning has changed the game in dermatology by using convolutional neural networks (CNNs) to handle and analyze complex visual data [25], [26]. Deep learning algorithms gain the ability to identify subtle patterns and features that correspond to different skin diseases by training on large sets of skin images. Two notable works that demonstrate this ability are [27] and [28]. Cutting-edge deep learning architectures such as Inception-V3, ResNet and DenseNet have been used to identify skin diseases with unprecedented accuracy. These studies highlight DL's exceptional ability to identify a wide range of skin disorders with an accuracy comparable to, or in some cases exceeding, human specialists. These conditions range from benign lesions to cancers such as skin cancer.

D. Deep Learning Methods to Identify Skin Disease

A. Using CNN to Identify Skin Diseases

CNNs, which provide previously unheard-of accuracy and efficiency, have transformed the process of identifying skin diseases. In [16] and [15], it is discussed how CNNs outperform traditional image processing techniques after being trained on skin image datasets. CNNs facilitate accurate classification and diagnosis of a variety of skin diseases by extracting complex patterns from images of skin lesions. As show in figure 10

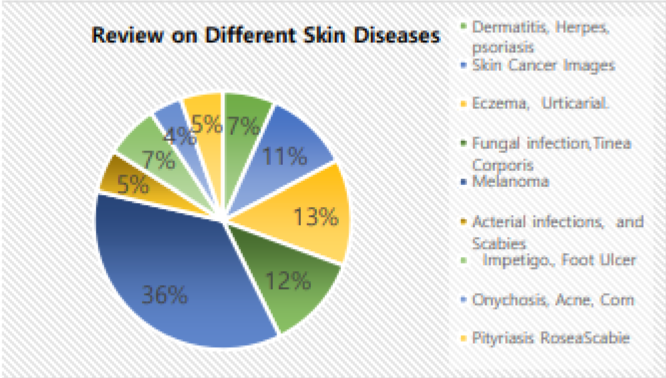

Figure 10. Various Skin Diseases [29].

B. Methods of Transfer Learning

Transfer learning techniques leverage pre-trained CNN models to enhance skin disease identification. [21], [30] demonstrate how to overcome the limitations of the scarcity of skin data by using models trained on large and diverse image datasets to improve the diagnostic performance of some skin disorders. As show in figure 11

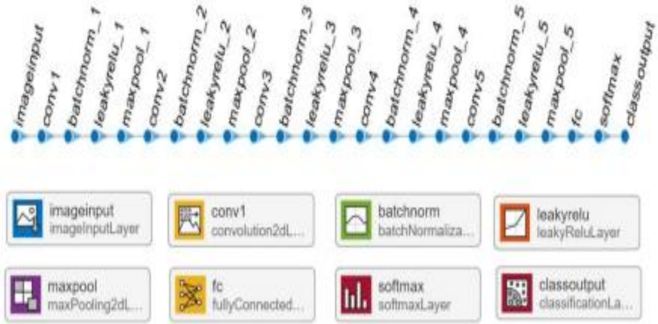

Figure 11. CNN Architecture of LWNet [31].

E. Data and Preprocessing

A. Overview of Skin Disease Datasets

Dermatology datasets have proven to be essential for training deep learning models. The size, quality and complexity of these datasets vary, as mentioned [19], [32], and they provide a variety of situations and lesion types that reflect the diversity found in the real world. This helps enable the creation of reliable diagnostic models. As show in figure 12

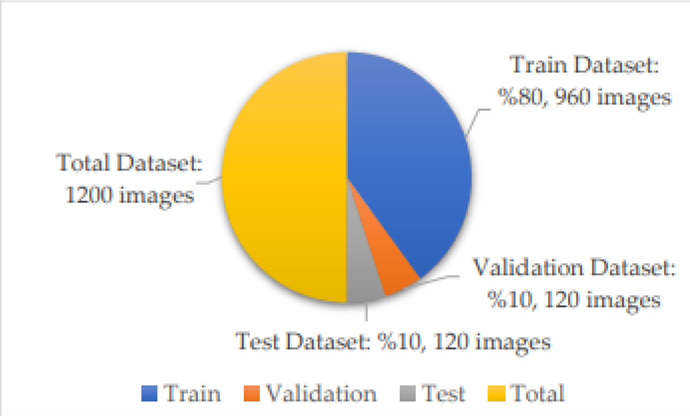

Figure 12. Distribution and Quantity of Datasets [30].

B. Preprocessing Techniques

In order to prepare datasets for deep learning models, preprocessing techniques are necessary. [14] Explains several techniques that improve data quality and representation to improve model training. These techniques, which include image enlargement, normalization, and segmentation, ensure that models acquire relevant patterns without overfitting.

F. Evaluation of Performance and Difficulties

A. Evaluation Standard

Evaluation criteria such as precision, precision, recall, and F1 score are essential for evaluating deep learning models. [16] Highlights the importance of these measures in evaluating the model's ability to accurately diagnose skin diseases and in guiding future validation and improvement of the model.

B. Obstacles to diagnosis using deep learning

Despite tremendous progress, deep learning-based diagnosis still faces many obstacles, such as class imbalance, model interpretability, and data scarcity. [24] , [21] emphasize ongoing initiatives to solve these issues, including creating more complex models, processing larger and more diverse data sets, and improving model transparency to enhance patient and physician trust.

G. Literature Review

Srinivasu et. al. in 2021 [33],used deep learning models, this study seeks to effectively classify skin diseases. It is proposed to integrate MobileNet V2 with long-term memory (LSTM) in this way. The results show that with faster processing and less computing effort, it performs better than other state-of-the-art models such as FTNN, CNN, and VGG. The proposed technique achieves over 85% accuracy using the HAM10000 dataset. Furthermore, a smartphone application has been created to quickly and accurately identify skin diseases. This helps in early detection of skin diseases by dermatologists and patients, reducing problems and morbidity.

Ding et. al. in 2022, [34],presented that there is wearable electronics require robust and flexible acoustic sensors with great sensitivity. MXene/poly (3, 4-ethlinesdiox-ythiophene)-poly (styrenesulfinate) (PEDOT: PSS) has been used by researchers to create a flexible pressure sensor in order to overcome the low flexibility and stability of MXene-based composites. The resulting sensor demonstrated impressive performance: it could detect speech, muscle movements, skin vibrations, and carotid artery pulsations. It also has a small profile (30 μm), great sensitivity, and fast response time (57 ms). Accurate speech recognition of various number pronunciations is made possible through integration with a deep learning model, suggesting potential uses in wearable electronic devices, health monitoring, and speech recognition.

Kousis et. al. in 2022 [35],presented that surpassed previous efforts with an impressive 92.25% accuracy, as it used a single lightweight deep learning model, DenseNet169, to achieve cutting-edge performance levels. In addition, a smartphone application has been developed that gives users the ability to differentiate between benign and malignant skin lesions and provides information on sun exposure parameters such as UV radiation, skin type, and sunscreen use.

Shaaban et. al. in 2023 presented that is no reliable way to detect skin cancer with traditional methods of detecting skin diseases. In order to improve accuracy, the deep learning-based method of this study makes use of the Inception-ResNet-v2 model and patient metadata. Including patient data improves classification accuracy by at least 5%, according to the results. Using a dataset of 57,536 dermoscopy images, this technique obtained an accuracy of 89.3%±1.1% in distinguishing between major skin diseases and 94.5%±0.9% in identifying benign versus malignant lesions.

Naeem et. al. in 2022 [37],presented that the SCDNet framework was created on the premise that early diagnosis of skin cancer is essential to increase survival rates. Vgg16 and CNN are combined for classification purposes in this framework. SCDNet outperformed other pre-trained classifiers with an impressive 96.91% accuracy for multiple classifications on the ISIC 2019 dataset. This demonstrates its potential to be a more accurate diagnostic tool for medical practitioners. Cost effectiveness and diagnostic quality are improved when deep learning is used in dermoscopy systems. However, there are still issues that require further study, such as the lack of a dataset for people with dark skin.

Tuwaijari et. al. in 2022 [38], presented that the Skin cancer is a fatal condition that must be detected early and treated effectively. Tumor variability presents problems although deep learning algorithms demonstrate the possibility of classifying melanoma from images. Using a dataset of 3297 dermatoscopy images, this study used three pre-trained models (DenseNet121, VGG19, and enhanced ResNet152). ResNet152 outperformed the other two models with an accuracy of 92% and an ROC score of 91%. Based on ResNet152, the Skin Cancer Recognition System (ResNetScr) was created, highlighting the value of early detection and the promise of deep learning to help detect and classify skin cancer.

Abbaraju et. al. in 2023 [39], presented that Early diagnosis of the disease is crucial in medicine, and cutting-edge computational methods such as CNN, RESNET, VGG, and EfficientNet can help diagnose monkey pox. However, due to the lack of data, especially images of affected skin, machine learning and deep learning have difficulty diagnosing monkeypox. In order to address this problem, a large collection of images of monkey pox skin was collected and used; this allowed VGG19 and ResNet to achieve an impressive 92% recognition accuracy. Although the need for large data sets and ethical constraints remain critical, these results demonstrate the ability of machine learning and particle learning models to accurately differentiate monkeypox and explore treatment alternatives.

Akram et. al. in 2023 [40], presented that In the Internet of Medical Things (IoMT), skin lesion analysis plays a crucial role in medical diagnosis. Using MRCNN and ResNet50 models, this study proposes a hybrid deep learning approach that combines semantic segmentation and lesion classification. The hybrid technique shows good classification reliability and identifies lesion boundaries with an accuracy of up to 95.49%. Its effectiveness is demonstrated through evaluation on the ISIC Challenge 2020 dataset, opening the door to a more precise study of skin lesions in IoMT as well as better diagnosis and medical care.

Azeem et. al. in 2023 [41], presented that is because of its diverse appearance and similarity to skin cancers, skin cancer can be difficult to diagnose. The goal of developing SkinLesNet, a new deep convolutional neural network, is to increase the accuracy and efficiency of classification. SkinLesNet consistently scores better than standard models such as ResNet50 and VGG16 in evaluations on various datasets. On the PAD-UFES-20-Modified dataset, SkinLesNet achieved an accuracy of 96%. By improving lesion classification, SkinLesNet has the potential to improve skin cancer diagnosis through further research.

Dhankar et. al. in 2023[42],presented that the skin conditions include toxic epidermal necrolysis (TEN), basal cell carcinoma, and melanoma, which are contagious and very serious. Although early detection is essential, diagnosing it correctly can be difficult and often requires consultation with a dermatologist. A non-invasive, easy-to-use skin disease detection tool has been developed to address this problem. It uses image processing, machine learning, and deep learning techniques. Using precise algorithms and image models for training, this tool achieves high accuracy and saves time and money. It has the potential to revolutionize dermatological investigations and reduce mortality rates.

Hammad et. al. in2023 [43],presented that to improve accuracy and efficiency compared to existing methods, this research introduces a new deep learning method called “Derma Care” for early identification and diagnosis of skin diseases such as psoriasis and eczema. The model outperforms the state-of-the-art techniques currently in use, as demonstrated by its 96.20% accuracy, high precision, recall, and F1 score. The model has the potential to improve skin disease detection and quality of life for those with it due to its ability to identify multiple skin diseases simultaneously. By working with medical professionals, future research can expand the model's capabilities to include a wider range of skin conditions and confirm its clinical effectiveness.

Omran et. al. in2023 [44],presented that focusing on skin cancer classification and data poisoning attacks, this paper presents a new method for secure federated learning in healthcare that leverages deep learning and the VGG16 CNN architecture. Data privacy is protected and ten healthcare organizations can collaborate on modular training by creating a single learning environment. The HAM10000 dataset, used in the MNIST skin cancer evaluation, demonstrates the model's specificity, accuracy, and resistance to attempts at data poisoning. The study focuses on data security and privacy in healthcare applications and presents a comprehensive technique to identify and thwart such attacks.

Islam et. al. in 2023[45], presented that is because monkeypox looks like other skin diseases, it can be difficult to diagnose correctly, which is the main focus of this study. The goal is to use deep learning models to develop a computer-aided detection system that can classify skin scans into normal, monkeypox, and other categories. The system collects a dataset of monkeypox skin lesions, applies preprocessing and data augmentation techniques, and then uses multiple deep learning models to reach an astonishing 99.52% accuracy. The study underscores how machine learning can be used to reliably and easily diagnose rare diseases such as monkeypox.

Jamil et. al. in 2023 [46], presented that this study aims to reduce the need for invasive biopsies while addressing the difficulty of correctly diagnosing skin cancer. The goal is to use data augmentation and transfer learning methods to build a deep learning model. The model performs admirably, outperforming other models with an F1 score of 0.854 and a specificity of 87.42%. These results demonstrate the success of the proposed method in diagnosing skin cancer.

Kaur et. al. in 2023 [47], presented that the difficulty of correctly diagnosing and classifying epidermolysis bullosa, an aggressive type of skin cancer, is the focus of this research. The goal is to create a deep learning model that enhances early detection and accurate classification of skin lesions. The proposed model provides remarkable accuracy and performance by combining hybrid and compression techniques. This work has remarkable potential to improve patient outcomes in the fight against epidermolysis bullosa and represents a major advance in skin disease detection.

Lu et. al. in 2023 [48], presented that the aim of this work is to fill the gap in deep learning algorithms for diagnosing disorders associated with skin hyperpigmentation. The goal is to find the best deep learning image recognition algorithm for accurate diagnosis. The results indicate that MobileNet has great accuracy and generalization ability that is useful in the adjuvant diagnosis of hyperpigmented skin. This study demonstrates how MobileNet can be used in clinical settings to diagnose different types of hyperpigmentation.

Nancy et. al. in2023 [49], presented that the goal of this research is to increase early detection of skin cancer caused by exposure to ultraviolet radiation as a result of global warming. Different deep learning (DL) and machine learning (ML) methods have been studied for the purpose of identifying and classifying skin lesions. In terms of accuracy, the Random Forest (RF) algorithm performed better than other machine learning algorithms, achieving 58.57% without augmentation and 87.32% with it. The accuracy of DL models, such as DenseNet, Inceptionv3, and MobileNetv2 ensemble, ranged from 77.92% to 98.02%. These results suggest the possibility of incorporating these approaches into clinical practice, if further study and validation are performed.

Mohamed et. al. in 2023[50],presented that accurate diagnosis and treatment of laryngeal cancer (LCA) can be difficult, especially when the disease is at an advanced stage. There are issues with accuracy, computational complexity, and scan time of existing methods. The paper presented the ALCAD-DMODL method that combines deep learning and dwarf mongoose optimization algorithm to solve this problem. Using filter-based preprocessing, EfficientNet-B0 for feature extraction, DMO for optimal parameter tuning, and MBGRU for classification, ALCAD-DMODL provides better results in LCA recognition and classification. This strategy is more effective than existing methods, as confirmed by evaluation using an image dataset of the throat region.

Marattukalam et. al. in 2023 [51], presented that this study underscores how little is known about wrist vein biometry compared to palm and finger vein biometry. The goal is to use deep learning methods to develop a contactless biometric identification system for wrist veins. The wrist vein pattern was successfully segmented, as evidenced by a DICE coefficient of 0.723 and an impressive F1 score of 84.7% for matching wrist vein images. Wrist biometric recognition is made affordable and efficient through the integration of subsystems.

Obaid et. al. in2023 [52], presented that the issue of accurate diagnosis and classification of skin cancer in light of the lack of advanced medical technology is the focus of this study. The goal is to develop a deep learning method that identifies skin cancer in images using CNNs. An accuracy of no less than 97.12% was achieved in predicting the type of skin that will form using the proposed model. This shows how CNNs can be a more useful technology than human visual assessment for early detection of skin cancer. The results underscore the need for further research and development in this vital area of medical diagnostics.

Obayya et. al. in 2023 [53], presented that this approach addresses the difficult early analysis of melanoma images caused by differences in lesion characteristics. The goal is to develop the best deep learning-based method for skin cancer classification and detection based on IoT. The proposed methodology performs better than existing models using a typical skin lesion database, with a maximum sensitivity of 97.74%, specificity of 99.71%, and accuracy of 99.55%. Our technology works better than current methods and has the potential to help dermatologists and other medical professionals.

Oztel et. al. in 2023 [54], presented that skin diseases can be difficult to diagnose because the skin lesions are very similar to each other. The purpose of this project is to develop a deep learning-based smartphone application for intelligent diagnosis of skin diseases. The system achieves 74.27% accuracy in seven-class classification on the combined dataset. By allowing patients to conduct early diagnosis using their smartphones, it promotes quick medical consultations. Upcoming initiatives include incorporating real clinical data, obtaining professional advice, and researching cross-platform mobile development strategies.

Raghavendra et. al. in 2023 [55], presented that this study addresses the problem of misidentification of malignant skin lesions. The goal is to develop an automatic recognition system using the leading Deep Convolutional Neural Network (DCNN) model. The proposed model achieves an amazing accuracy of 97.20%, superior to other advanced models. It shows excellent accuracy, ROC-AUC score, F1 score, and memory. It seems possible to support clinical decision making using a GUI as a system.

Bizel et. al. in 2024[56], presented that this study attempts to address the issue of how current apps inaccurately classify skin disorders for users with different skin tones, especially those with darker skin tones. The goal of the study was to increase classification accuracy and enable a range of groups to receive a skin cancer diagnosis using a deep learning algorithm. By analyzing visual searches for skin-related health queries, the study effectively complemented the findings, providing consumers with health-related digital visual search results that correctly reflect the range of skin tones seen in the American population.

Ghosh et. al. in 2024[57], presented that this study focuses on the problem of accurate classification and diagnosis of skin cancer at an early stage. The goal is to use deep learning (DL) techniques, such as CNN, VGG16, ResNet50, and InceptionV3, to recognize and classify different skin diseases. According to the results, DL is useful in early detection and staging of skin cancer, which may benefit dermatologists and enhance patient outcomes. Further advances, such as data preprocessing and development of hybrid models, are needed to increase the flexibility and accuracy of melanoma diagnosis.

Journal et. al. in 2023 [58], presented that the problem of expensive and limited medical equipment for rapid diagnosis of skin diseases is the focus of this study. The goal is to use deep learning algorithms to help with early recognition and diagnosis of skin problems. The study achieved 70% (CNN) and 80% (AlexNet) classification accuracy for melanoma, nevus, and seborrheic keratosis using a dataset of 938 images. The results demonstrate that artificial neural networks can recognize and classify skin diseases, suggesting that certain changes in the network architecture are needed to increase effectiveness.

Parashar et. al. in 2022 [59], presented that the purpose of this work is to improve skin disease detection and diagnosis through the use of deep learning techniques, specifically with respect to the VGG19 and Inception ResNetV2 models. The results show an amazing ability to distinguish subtle differences in shape, color and texture across a variety of skin types. The models offer an automatic and accurate way to diagnose skin problems, which has the potential to revolutionize the field. Applying the latest AI technologies in dermatology can improve patient outcomes and diagnostic performance.

Ivanov et. al. in 2024[60], presented that the study aimed to identify and describe skin abnormalities, reduce inter-patient variability, and enhance conventional histological analysis. The goal was to improve diagnostic judgment and develop digital histology for clinical applications. The end result was the development of a deep learning model with a classification accuracy of 92% that demonstrated the ability to identify and differentiate between normal and abnormal skin tissue. The study highlighted the importance of computational time as well as the possibility of expanding digital tissue analysis in the future through the use of a larger data set.

Rajendran et. al. in 2024[61],presented that this effort attempts to provide a solution to the problem of using endoscopic images to identify skin cancer. The study aims to develop ASCDC-CSODL, an automated deep learning and swarm optimization system for melanoma detection and classification. The ASCDC-CSODL technique leveraged: segmentation from U-Net, skin tumor classification from gated recurrent unit (GRU), denoising from binary filtering, and feature extraction from MobileNet. The results of the study showed a noticeable improvement in performance compared to other methods, as accuracy rates in the two data sets reached 97.44% and 98.48%.

Taspinar et. al. in 2024 [62], presented that finding quick and accurate ways to diagnose diseases caused by viruses, such as monkeypox, has become more important as these diseases spread around the world, especially in light of the COVID-19 pandemic. The goal of this work was to use deep learning architectures to predict skin lesions in individuals infected with monkeypox. A dataset of different infections and skin diseases was used for image classification using two CNN models, VGG16 and VGG19. Based on the results, the VGG19 model achieved the best classification accuracy of 97.81% in identifying skin lesions associated with monkeypox. Through fine-tuning, the model's performance was further improved, exceeding the results of previous studies and proving useful in classifying skin lesions associated with monkeypox. The study recommends using machine learning and image processing to create decision-assistance systems.

Zhao et. al. in 2024[63], presented that this work addresses the problem of insufficient clinical context for classifying melanoma lesions using deep learning techniques. The goal is to develop custom models that address problems such as imbalanced data sets and diverse skin types. The results show that the proposed models outperform existing models, especially in classifying lesions from minority groups, and that they enhance diagnostic accuracy by applying ensemble model methodologies. This research contributes to the advancement of artificial intelligence in diagnosing skin diseases by providing accurate diagnostic tools that improve patient outcomes.

Kashyap et. al. in 2024 [64], presented that limited access to health care in rural settings and the high cost and duration of diagnostic procedures make it difficult for doctors to make an accurate diagnosis of skin diseases. To overcome this, a multi-layer convolutional neural network model was developed that can differentiate between skin diseases and healthy skin using input images. The model's astonishing accuracy suggests that automated detection of skin diseases may be possible. This simplified approach allows rapid and accurate diagnosis, promoting early intervention and treatment for a range of skin diseases.

Table 1. Related Work Summary

Reff	Year	Methods	Dataset	Advantage	Disadvantage	Accuracy
[33]	2021	Deep learning	HAM10000	Effectiveness and flexibility	There's not a lot of uncertainty. Improvement is necessary.	>85%
[34]	2022	Deep learning and manufacturing	big quantities	Outstanding work	Limited ability to adapt	High (91%)
[35]	2022	Deep learning	HAM10000	Mobile application	Efficiency problems	92.25%
[36]	2022	Deep learning	HAM10000	Enhance output	Restricted data set	89.3% (four major skin problems), 94.5% (benign versus malignant lesions)
[37]	2022	Deep learning	2019 International Standard Industrial Classification	Excellent production	Restricted generalization	Intelligent data storage network: 96.91%; Competitors: Various

[38]	2022	Models created using deep learning methods.	Instant detection	Enhance efficiency	Not a valid classification	92%
[39]	2023	Algorithms derived from machine learning (ML) and deep learning (DL).	The dataset contains images of skin infected with monkeypox.	Enhance classification results	Restrict access to data	92%
[40]	2023	Combining deep learning methods	Images taken by dermatoscopy	Improve accuracy	The segmentation performance of existing approaches is poor, which may lead to a decrease in classification accuracy.	95.49%, 96.75%
[41]	2023	Advanced convolutional neural network	Modification of PAD-UFES-20, HAM10000 and ISIC2017	Diagnostic effectiveness	Complex skin lesions	96%, 90%, 92%
[42]	2023	Image-based machine learning, Deep Learning	PAD-UFES-20 is in-depth	Simple and unobtrusive to use	Limitations of the data set	Minimal error
[43]	2023	Deep learning	Wide and varied	Excellent accuracy	Restricted data set	96.20%
[44]	2023	Deep learning	HAM10000 dataset for skin cancer classification	Safe and accurate	data tainting	High
[45]	2023	Deep Learning	Data set of skin lesions caused by monkeypox	Identify rare diseases	Limited data availability	99.52%
[46]	2023	Deep learning	ISIC Challenge 2018 (images of skin lesions)	precision of diagnosis	Possible prejudices	Specificity 87.42% and F1 score of 0.854
[47]	2023	Deep learning	Skin cancer pictures	Promote accurate measurements	Variation in data	Enhance accuracy
[48]	2023	The algorithms are developed using deep learning methods.	Pictures of skin diseases	Neutral evaluation	Lack of deep learning algorithms to diagnose diseases causing skin hyperpigmentation.	Very accurate

[49]	2023	ML/DL	ISIC database/Accessible datasets	Early recognition	The length of time spent	Accurate classification
[50]	2023	Deep Learning	Pictures of the throat area	Simple to understand and effective	Extended analysis	Outstanding accuracy
[51]	2023	Deep learning	Related data set for vein patterns in the wrist	Low cost and touchless	LED brightness variations require optimization of Siamese neural networks.	Approximately 0.723 dice coefficient and 84.7% F1 score
[52]	2023	Deep learning (DL)	Dataset HAM10000	Improve identification	Unable to provide an accurate diagnosis	97.12%
[53]	2023	Deep learning (DL)	ISIC skin lesion database	Enhance output	Enhance output	99.55%
[54]	2023	based on deep learning	A piece of data combined	Ability to adapt to mobile devices	Real-world clinical data	74.27%
[55]	2023	Deep convolutional neural network or DCNN	HAM10000	Accurate identification	Not enough data available.	97.20%
[56]	2024	Deep learning/CNN	skin cancer	Unexpected words	Inadequate implementation	High
[57]	2024	Deep learning (DL)	Skin diseases	Output features	Class division	Improve results
[58]	2024	Deep Learning (DL)	Skin diseases	Faster diagnosis and less labor	Limited space for development and medical supplies	70% (using CNN), 80% (using AlexNet)
[59]	2024	Deep Learning (VGG19 Receiver, ResNetV2)	Various skin conditions	Automated diagnosis with high accuracy and the possibility of early intervention	The need for continuous investigation and progress	Superior metrics for F1 score, recall, precision and precision
[60]	2024	Deep learning and Muller polarity	Skin aging and malignant tumors	It overcomes patient variability, facilitates digital	training computation time, necessitating a larger sample size and a larger data set.	Classification accuracy 92%

				histological analysis, aids in the process of making a diagnosis, and helps in detecting abnormalities on the skin.		
[61]	2024	Computer Vision (CV) with Deep Learning (DL)	Using endoscopic images to detect skin cancer	Improved results, automatic classification and detection	Computational complexity	97.44%, 98.48%
[62]	2024	Deep learning	Pictures of wounds on the skin	High accuracy	Complex sample	97.81%
[63]		Deep learning	Pictures of lesions caused by skin cancer	good job	Unbalanced data collection	High
[64]		CNN or convolutional neural network	Skin diseases	Fast, accurate and computerized diagnosis	There were a few skin diseases among them.	Eczema accounts for 96.27% of cases, nail fungus 86.75%, skin cancer 96.73%, bullous pemphigoid 85.64%, and hemangiomas 84.22%.

H. Discussion

The use of deep learning in skin disease detection has yielded encouraging results, with notable improvements in accuracy, efficiency, and model evolution from 2021 to 2024. This field of study is constantly changing due to the use of diverse datasets and methods and the goal of solving the difficulties inherent in disease diagnosis. Dermatology. A strong foundation has been created by early research by [9] and [8], who achieved accuracy rates of over 91% and over 85%, respectively. Their work highlights the potential to improve the accuracy of skin disease diagnosis by demonstrating the effectiveness of deep learning in robustly handling large data sets [8][9][10] and [11] have demonstrated the gradual progress in this field by achieving an accuracy of 92.25% and 94.5%, respectively. They accomplished this by using the HAM10000 dataset to distinguish between benign and malignant lesions, among other difficult skin disorders. [12] made a major breakthrough when he revealed that the SCDNet model could achieve 96.91% accuracy. This was a noteworthy achievement that demonstrated the superiority of custom deep learning models in identifying skin diseases [12]. Even with these successes, research has acknowledged persistent problems such as model efficiency and data set limitations. In order to increase diagnostic performance, [13] and [15] showed outstanding accuracy of 92% and 95.49%, respectively. However, they also highlighted the need to enhance the diversity of datasets and the generalizability of models. This trend toward increasingly complex deep learning architectures continues in 2024. Using advanced models such as AlexNet and VGG19, Journal, Parashar and Taspinar were able to achieve accuracy levels of up to 97.81%. By combining cutting-edge computational techniques for solving problems with the diversity of data sets and generalizability of models, this research [32][33][36][65][66][67]reflects the cutting edge of overcoming previous limitations. As a result, the path of deep learning skin disease identification is characterized by a steady increase in diagnostic capabilities, with an emphasis on solving problems of model generalization, computational efficiency, and dataset diversity. The combined results for 2021-2024 show how deep learning can be more deeply integrated into clinical dermatology, signaling a time when AI will not only aid in the diagnostic process, but also significantly enhance it.

I. Conclusion

The increasing incidence of skin cancer, especially melanoma, which is the deadliest type among its various forms, has emerged as a major global health problem. Not only has this increased the prevalence of skin cancer, it has also highlighted how important it is to recognize the disease early and accurately stage it in order to improve treatment outcomes and patient survival rates. Traditional diagnostic methods, which rely mostly on visual inspection and judgment by medical experts, have major drawbacks. These difficulties result from the intrinsic heterogeneity in the manifestations of skin lesions and the global lack of dermatological knowledge, especially in resource-limited areas. Thus, there is an urgent need for innovative diagnostic approaches capable of overcoming these limitations by increasing diagnostic accuracy and accessibility. In order to address the above problems, this review paper investigates how to integrate artificial intelligence (AI), especially deep learning (DL) and convolutional neural networks (CNNs). Thanks to advanced neural network topologies and algorithms, CNNs and DL networks have shown remarkable ability in analyzing and interpreting dermoscopic images. This study aims to explore the potential of these AI models to transform skin cancer diagnosis through the use of large dermatoscopy image data sets, with a focus on their use in early identification and classification of skin cancer types. Our comprehensive literature analysis carefully examines the latest developments in AI-assisted skin disease identification, focusing on the use of CNNs and DL in making diagnosis. We investigated a number of papers that have used AI algorithms to diagnose skin cancer, and closely examined the methods, model architectures, data preprocessing methods, and, above all, performance metrics of these AI models. The selected studies, covering the years 2021-2024, demonstrate the rapid progress and increasing reliance on artificial intelligence in diagnosing skin diseases. Muhammad et al. (2023) showed that models combining deep learning (DL) with new techniques such as reinforcement learning achieved impressive results, with an 80% accuracy rate in classifying skin cancer into seven different categories. This method not only demonstrates how DL and CNN can be used to overcome the limitations of traditional diagnostic techniques, but also highlights how AI-based tools are always evolving to improve the diagnosis of skin diseases. Our review also highlights the vital role these technologies play in enabling accurate and timely diagnosis and classification of skin disorders, which may lead to better patient outcomes. This paper provides a comprehensive overview of the status of AI applications in skin cancer detection by combining the findings of the reviewed literature. He explains how AI is a ray of hope in the ongoing battle against skin cancer, especially using DL and CNN. Additionally, it provides insightful conversations about the difficulties encountered—such as lack of data, heterogeneity in segregation, and requirements for interpretability of models—as well as the ways in which current research projects are solving these problems. Ultimately, this review paper highlights the bright future of further integration of AI into clinical dermatology, leading to a new era in which AI not only enhances the diagnostic process but also complements it, leading to a paradigm shift in dermatology patient care and outcomes.

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