Advances in Skin Cancer Detection Using Machine Learning: Current Methods and Future Directions

Abstract

With increasing incidence rates, high mortality risks, and substantial cost burdens, skin cancer is a serious global health concern. In order to improve patient outcomes, early and accurate detection is essential. Due to their heavy reliance on clinical knowledge, traditional diagnostic techniques are prone to subjectivity. In order to overcome these obstacles, automated skin cancer diagnosis has been using machine learning (ML) and deep learning (DL) models more and more. Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and ensemble learning models are among the ML and DL models that are methodically assessed and contrasted in this study for their ability to classify skin lesions. We examine how classification performance is affected by preprocessing methods, optimization tactics, and dataset selection. More specifically, this study makes use of publically accessible benchmark datasets including PH2, ISIC, and HAM10000 to guarantee a thorough assessment of model effectiveness. Our results show the benefits and drawbacks of various approaches, offering guidance for creating AI-driven diagnostic tools that are more precise, understandable, and useful for actual clinical settings.

Keywords: Skin Cancer Detection, Machine Learning, Deep Learning, Convolutional Neural Networks (CNNs).

I. Introduction

Dermatological problems are among the most prevalent health concerns globally. Skin cancer is generally classified into two main categories: melanoma and non-melanoma. Melanoma is a dangerous and lethal form of skin cancer[1]. Melanocytes are the cells in which melanoma develops. The process starts when healthy melanocytes undergo uncontrolled proliferation, leading to the formation of a malignant tumor. It may impact any area of the body. Melanoma skin cancer, although comprising less than 1% of all cases, has a very high death rate. Prompt intervention for skin can enhance five-year survival rates by around 14%[2]. Artificial intelligence (AI), a discipline within computer science that employs computers and software to replicate intelligent human behavior using a variety of technologies, is a pivotal catalyst of the fourth industrial revolution. Machine learning (ML) is an artificial intelligence approach that use statistical models and algorithms to incrementally learn from data, enabling the prediction of attributes of fresh samples and the execution of specified tasks. Consequently, intricate algorithms are developed to execute activities that would otherwise pose challenges for human cognition. Convolutional Neural Networks (CNNs) mimic neuronal functions and are widely used for pattern recognition in medical imaging A convolutional neural network (CNN) is a form of machine learning that mimics the functioning of real neurons and represents the leading architecture for pattern identification in medical image analysis. Artificial intelligence is set to revolutionize healthcare due to its superiority over conventional analytical methods. There is increasing excitement over the uses of AI in healthcare, including enhancements in medical diagnostics, therapy, and administrative support to expedite new drug development timeframes. It may also serve as an adjunct in clinical decision-making. The efficacy of deep learning is ascribed to its capacity to independently extract semantic information from large datasets[3]. Timely diagnosis is the important element in the treatment of skin cancer[4]. Physicians frequently utilize the biopsy technique to diagnose skin cancer.

A) Challenges in Skin Cancer Detection

Skin cancer diagnosis poses several challenges for patients and healthcare professionals:

1)Visual Assessment: The visual assessment of cutaneous lesions may be subjective, resulting in possible inaccuracies and misdiagnoses. Differentiating between benign and malignant tumors can be difficult, even for seasoned dermatologists.

2) Limited Access to Dermatologists: The availability of dermatologists may be restricted in some places, resulting in prolonged waiting periods for appointments and delays in diagnosis and treatment. This can negatively impact patient outcomes and survival rates.

3) Misdiagnosis: Misdiagnosis or neglect of skin cancer can delay treatment, worsening patient outcomes. The accuracy of diagnosis may vary depending on the healthcare provider's experience and the accessibility of diagnostic instruments. Existing Protocols for Skin Cancer Diagnosis: At now, the identification of skin cancer predominantly depends on visual assessment and biopsy. Dermatologists conduct visual examinations of worrisome skin lesions, frequently employing dermo copy, a method that enhances the skin's surface for meticulous analysis [5] [6] A biopsy is conducted, if required, to obtain a tissue sample for further examination by a pathologist.

B) Role of Machine Learning in Skin Cancer Detection

Machine learning (ML) enhances skin cancer identification and diagnosis[7]. Machine learning algorithms can analyze large photos and clinical information datasets to detect patterns and signs of skin cancer. Here is how machine learning might enhance skin cancer diagnosis:

1) Automated Image Analysis: Machine learning algorithms can evaluate photographs of skin ML algorithms analyze skin lesion images, comparing them with established cases to determine malignancy probability[8]. This can assist in detecting anomalous lesions that may necessitate more investigation.

2) Decision Support Systems: Machine learning algorithms can offer decision support to dermatologists by proposing diagnoses or assessing the probability of malignancy based on input data. This assists healthcare workers in making educated judgments regarding patient care treatment paths[9].

3) Telemedicine and Remote Consultations: Machine learning-based image analysis may be incorporated into telemedicine platforms, facilitating remote consultations between patients and dermatologists. This is especially advantageous in underdeveloped regions where access to dermatological care is limited[10].

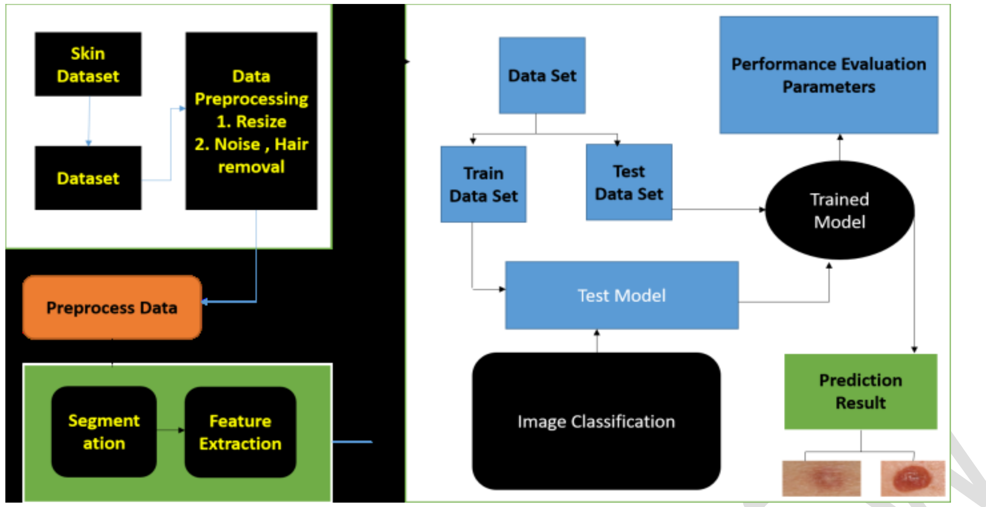

Figure 1 Methods for diagnosing skin diseases[2]

Figure 1: Overview of diagnostic methods for skin diseases, illustrating the key steps in traditional and AI-based detection approaches. This visual highlight the transition from manual clinical diagnosis to automated machine-learning techniques

Skin cancer symptoms may be rapidly, accurately, and safely identified with computer technology. The conventional technique for diagnosing skin cancer is obtaining the pre-processed picture, segmenting it, extracting features, and then classifying it, as seen in Figure 1.

This paper's goal is to present a thorough analysis of the developments, difficulties, and potential paths in the use of machine learning for skin cancer diagnosis. It aims to assess the efficacy of present approaches, pinpoint important research gaps, and offer practical suggestions to raise diagnostic precision and effectiveness. The study emphasizes how machine learning algorithms might transform healthcare procedures and improve patient outcomes by integrating them into the detection and treatment of skin cancer[11].

The remainder of this paper is structured as follows: Section II provides an overview of skin diseases and their significance in healthcare. Section III explores the basics of machine learning and deep learning, setting the foundation for their applications in skin cancer detection. Section IV discusses algorithms used in machine learning for diagnosing skin cancer, while Section V focuses on the role of deep learning in advancing detection techniques. Section VI reviews related work in this domain, and Section VII presents a comparative analysis through a related work table. Section VIII offers a discussion of the findings and their implications, and Section IX concludes the paper with key takeaways and directions for future research.

II. SKIN DISEASE

The skin, the biggest organ of the human body, consists of three layers: the epidermis, dermis, and hypodermis. The skin's three principal functions—protection, sensibility, and thermoregulation—render it an effective barrier against environmental hazards. Melanocytes in the dermis produce the pigment known as melanin. Melanocytes augment melanin production, acting as barriers that protect the skin from the harmful effects of ultraviolet (UV) radiation. Abnormal proliferation of melanocytes results in melanoma. The three principal forms of skin cancer are basal cell carcinoma, squamous cell carcinoma, and malignant melanoma (MM). Both of the aforementioned are also referred to as keratinocyte carcinomas[2].

Figure 2 Classification of dermatological disorders:[2]

Keratinocytes (KC) originate from basal and squamous keratinocytes. Despite potential exaggeration, these numbers indicate the most common kind of skin cancer in both genders.

(Figure 2) illustrates the many categories of dermatological conditions. Melanoma is acknowledged as the worst form of skin cancer, with a death rate of 1 in 62 occurrences relative to other skin cancer kinds. Melanoma frequently manifests as alterations in the dimensions, form, or pigmentation of pre-existing moles. They may also manifest as odd, atypical cutaneous lesions. The ABCDE rule aids in recognizing possible indicators. Asymmetry: One half differs from the other. Border anomaly: Irregular or serrated edges, color variations: Diverse hues of brown, black, red, or white. Diameter: generally, exceeds that of a pencil eraser. Evolution: Incremental alterations in dimensions, shape, or attributes.

III. Basics of Machine Learning and Deep Learning

Artificial intelligence may be classified into three categories based on a technology-oriented paradigm. artificial narrow intelligence, global artificial intelligence, and artificial superintelligence[12]. Narrow AI is proficient at executing a certain job with intelligence. Narrow AI is utilized most frequently. General AI possesses the ability to do any cognitive task akin to that of a human. Super AI may surpass human skills and perform any task more effectively than humans with cognitive attributes. Machine Learning is a subset of Artificial Intelligence in which computer systems acquire knowledge from encounters without explicit programming. A supervised, semi-supervised, or unsupervised methodology may be employed. The computer is provided with datasets of issues and solutions in a supervised manner. Machines acquire the ability to choose the appropriate answer through experimentation and correction. In unsupervised learning, machines evaluate incoming data without a predefined answer.Semi-supervised learning is a technique that employs both labeled and unlabeled data[13]. Deep learning is a subset of machine learning that employs numerous layered deep neural networks, each capable of identifying and learning certain properties inherent to the dataset[14],[15]. The fundamental kind of artificial neural network is the feedforward neural network. The structure comprises three layers: input, hidden, and output, through which data enters via the input layer, traverses the hidden layer, and exits through the output nodes. Numerous concealed layers are feasible [16]. Convolutional Neural Networks (CNNs) are a type of deep, feed-forward artificial neural network primarily employed for the analysis of visual information. It comprises convolutional and pooling layers that enable the network to encode image features[17].

IV. Algorithms for Machine Learning in Skin Cancer

Due to the elevated incidence of cutaneous cancers, a growing number of individuals require timely diagnosis and continuous surveillance[18]. This imposes significant pressure on specialized medical services, which might be mitigated by improved patient self-monitoring methods and the use of decision support technologies for less experienced clinicians. Machine diagnosis is objective and unaffected by environmental influences. Nevertheless, human diagnosis is prone to subjective variances and may be influenced by external variables. With the appropriate laws in place, the application of Machine Learning for detecting and monitoring skin cancer might lead to a reduction in the number of biopsies performed. After a training intervention, patients with skin cancer and their caregivers are capable of doing self-skin examinations (SSE). This also enhances teledermoscopy, resulting in a reduction in medical consultations. The integration of AI in smartphone applications can educate individuals on doing skin examinations and relay the findings to the physician. Each type of skin lesion is categorized into classes, such as "benign" and "malignant," or "naevi" and "melanoma," to develop a novel machine learning algorithm for skin cancer. Deep learning algorithms are trained on a substantial dataset of images within each category prior to assessment on a novel image. The process consists of three fundamental components. In the initial phase, the algorithm is provided with digitized macroscopic or dermoscopic pictures annotated with the "ground truth," which, in this context, refers to the lesion diagnosis established by a qualified dermatologist or through histological examination. During stage 2, convolutional layers derive the feature map from the pictures. A feature map is a visual depiction of data that encompasses many levels of abstraction. The initial convolutional layers extract fundamental information like as edges, corners, and shapes. Subsequent convolutional layers extract advanced features to identify the kind of skin lesion[19]. The machine learning classifier utilizes the feature maps in stage 3 to identify various types of skin lesion patterns. A new image may now be categorized utilizing the deep learning technique[20]

V. Deep Learning in Skin Cancer Detection

Deep learning has shown promise in the area of skin disease diagnosis and detection. Leveraging the capabilities of deep neural networks, researchers and developers have explored various approaches to improve the accuracy and efficiency of skin disease detection. A Convolutional Neural Networks (CNNs) are broadly used for image classification tasks, in-cluding the identification of skin diseases from medical im- ages [21]. These networks can learn hierarchical features from dermatological images, enabling them to distinguish between different skin conditions. Dermoscopy involves examining skin lesions using a dermatoscope, providing detailed images for analysis. Deep learning models, especially CNNs, have been employed to analyse dermoscopic images for the detection of melanoma and other skin diseases. Some models can achieve performance comparable to or even exceeding that of dermatologists. Due to the limited availability of labelled medical data, Data augmentation techniques are frequently used to artificially increase the training dataset. This helps improve the generalization ability of deep learning models and enhances their performance on new, unseen cases. In Transfer Learning Pre-trained deep learning models on huge datasets, like ImageNet, can be improved for the identification of skin diseases. Applying Knowledge from one activity to improve performance on a similar task with limited labelled data is known as transfer learning. The Visual Geometry Group at the University of Oxford invented the VGG16 and VGG19 networks, which are well-known for their effectiveness and simplicity. Convolutional network with 13 layers and three fully linked layers make up the sixteen weight layers of VGG16. The convolutional layers employ small 3x3 filters, while the max-pooling layers utilize 2x2 pooling windows with a stride of 2. ResNet introduced residual learning, making it easier to train very deep networks. Some popular variants of ResNet include (ResNet-18, 34, 50, 101, and ResNet- 152), with the numbers indicating the depth of the networks. Ensemble Methods Combining the predictions of multiple deep-learning models can enhance overall accuracy. Systems for detecting skin diseases can be made more resilient and reliable by using ensemble techniques like boosting or bag- ging. Explain ability Interpretable deep learning methods are vital in the medical domain to provide explanations for their predictions. Multi-modal Approaches Combining information from various sources, such as clinical data, patient history, and imaging, can enhance overall diagnostic accuracy. Integrating different modalities with deep learning models offers a comprehensive approach to skin disease detection. Deployment in Clinical Settings for the practical implementation of deep learning models in healthcare, considerations such as regulatory compliance, data privacy, and integration with existing clinical workflows need to be addressed[22]. Collaboration between machine learning experts and healthcare professionals is crucial for successful deployment.

VI. Literature review

Over the last few years, deep learning and machine learning have taught us a lot about skin diseases. These technologies have especially helped us learn how to automatically find and name skin flaws. A lot of study groups have looked at CNNs, transfer learning models, and ensemble learning methods, among other things. Many changes have been made that hurt these and make them less useful and right. To check how well these models work, normal datasets like HAM10000, ISIC, PH2, and DermNet were used. Through data improvement, preprocessing, and optimization methods OK, it has also been used to build bigger models and fix class mismatches. Some models that are easy to understand and believe are those that use explainable AI (XAI) methods and mixed learning systems, along with feature extraction techniques. This part talks about and shows how machine learning is being used to put skin diseases into groups. Models, samples, and success measures like these were used in the most recent big group study.

Vatsala Anand et al. (2022)[23] Performed an extensive analysis of four pre-trained transfer learning convolutional neural network models (DenseNet121, ResNet50, VGG16, and ResNet18) for the categorization of skin diseases utilizing dermoscopy pictures from the HAM10000 dataset. The dataset comprises seven classes of skin diseases, and the study employed data augmentation approaches to mitigate class imbalance. The trials employed two batch sizes (16 and 32) and two optimizers (Adam and SGD). ResNet50 and ResNet18 exhibited optimal performance with a batch size of 32 and the SGD optimizer, with accuracies of 90%. DenseNet121 attained an accuracy of 89% and had superior sensitivity (94%) for Basal Cell Carcinoma. This automated system, characterized by its superior performance and practical applicability, was suggested as a supplementary diagnostic tool for dermatologists.

Ignatious K. Pious and Dr. R. Srinivasan (2022)[24] Performed a comparative comparison of classification methods for the early identification of skin cancer utilizing a dataset including 3,500 dermoscopic pictures. The research assessed five models: CNN, SVM, VGG16, ResNet50, and ViT. The

CNN model had the highest performance, with an accuracy of 97.61%, followed by ViT at 84.31%, SVM at 83.48%, VGG16 at 82.49%, and ResNet50 at 50.05%. The preprocessing stages include scaling photos to a uniform dimension, hair extraction, and data augmentation. The findings underscore CNN's preeminence in the identification of early-stage skin cancer, positioning it as a viable method for clinical use.

Karthik Ra et al. (2022)[25] presented Eff2Net, an effective convolutional neural network (CNN) utilizing channel attention for the categorization of skin diseases. The model utilizes the EfficientNetV2 architecture, substituting Squeeze-and-Excitation (SE) blocks with Efficient Channel Attention (ECA) blocks. This alteration substantially decreases the trainable parameters to 16 million while preserving superior performance. Eff2Net categorizes four dermatological conditions—acne, actinic keratosis, melanoma, and psoriasis—utilizing a dataset of 4,930 photos augmented to 17,329 by data enhancement techniques. The model attained an overall accuracy of 84.7%, surpassing current state-of-the-art models while maintaining a balance between accuracy and computational complexity. This method highlights the compromise between efficiency and efficacy in medical picture categorization.

V. Auxilia Osvin Nancy et al. (2023)[26] performed an extensive comparative investigation of machine learning (ML) and deep learning (DL) algorithms for skin cancer diagnosis. The study emphasizes the efficacy of several machine learning algorithms, notably Random Forest (RF), which attained accuracies of 58.57% without augmentation and 87.32% with augmentation. Among deep learning approaches, MobileNetV2 and an ensemble of DenseNet and InceptionV3 demonstrated exceptional performance, achieving accuracies of 97.58% and 97.50%, respectively, following the application of augmentation. A tailored CNN model with diverse layers and hyperparameter optimization attained an accuracy of up to 98.02%. The investigation utilizing the ISIC archive datasets underscores the significance of augmentation approaches, pre-processing, and feature extraction in improving model performance. The research highlights the efficacy of transfer learning in attaining elevated accuracy and advocates for more investigation into clinical integration.

Gurpreet Singh et al. (2023) [27]Developed a refined pre-trained VGG16 model for the binary classification of skin disorders (benign and malignant) with a dataset of 44,000 pictures. The technique included preprocessing photos to a standardized size of 224x224, implementing data augmentation, and optimizing hyperparameters such as learning rate, epochs, and batch size. The model attained an accuracy of 90.1%, with a precision of 0.867, recall of 0.942, and an F1-score of 0.891, indicating its efficacy in differentiating skin disorders. The VGG16-based method surpassed previous models in classification accuracy, demonstrating efficacy for early diagnosis and enhancing dermatological results.

NandaKiran Velaga et al. (2023)[10] Performed a comparative comparison of machine learning models for the classification of skin lesions utilizing the HAM10000 dataset. The research evaluated five machine learning algorithms: K-Nearest Neighbors (KNN), Decision Tree, Random Forest, Ridge Classifier, and Support Vector Machine (SVM). The dataset underwent preprocessing to rectify class imbalance by the application of the Synthetic Minority Oversampling Technique (SMOTE). The Random Forest classifier had the highest performance among the assessed models, attaining a test accuracy of 95.6% and a validation accuracy of 95.5%. The research underscores the efficacy of ensemble learning methods, including Random Forest, for dependable and precise skin cancer identification. This study highlights the efficacy of machine learning methods in facilitating early identification and supporting dermatological decision-making.

Syed Inthiyaz et al. (2023)[28] Proposed an automated method utilizing deep learning for the categorization and diagnosis of dermatological conditions from dermoscopic pictures. The model employs Convolutional Neural Networks (CNNs) for feature extraction and classification, utilizing a softmax classifier to differentiate between benign and cancerous pictures. The research analyzed a dataset of 150,223 photos from Xiangya-Derm, the most extensive compilation of skin disease photographs, and scaled the images to 227x227 pixels for optimal processing efficiency. The model attained an accuracy of

87.42%, demonstrating enhancements above current techniques. The approach emphasizes the possibility for affordable, scalable, and instantaneous diagnostic tools, especially beneficial in resource-limited environments.

Gurpreet Singh et al. (2023) [29]developed a rigorously tuned pre-trained VGG16 model for the binary classification of skin conditions into benign and malignant categories. The model was trained on a dataset including 44,000 photographs sourced from Kaggle, employing preprocessing techniques to resize images to 224x224 pixels and applying data augmentation to improve generalization. The model achieved an accuracy of 90.1%, precision of 0.867, recall of 0.942, and an F1-score of 0.891 by employing transfer learning on the VGG16 architecture. Compared to earlier models such as DenseNet and ResNet, the fine-tuned VGG16 demonstrated superior performance, establishing it as a feasible choice for the early detection and management of skin diseases. The study highlights the potential of employing transfer learning for efficient and dependable classification in medical imaging.

Sarvachan Verma and Manoj Kumar (2024) [2]Proposed a hybrid machine learning model for the classification of skin disorders utilizing discrete wavelet transform (DWT) and gray-level co-occurrence matrix (GLCM) for feature extraction. The model integrates three classifiers—Support Vector Machine (SVM), Decision Tree (DT), and k-Nearest Neighbor (KNN)—within an ensemble learning framework to categorize skin disorders as benign or malignant. The HAM10000 dataset, consisting of 10,015 pictures, was utilized for training and assessment. The model attained an accuracy of 95.50%, surpassing the performance of individual classifiers (SVM: 85.00%, KNN: 90.00%, DT: 95.00%). The research underscores the efficacy of DWT and GLCM in deriving significant texture characteristics and accentuates the model's resilience and efficiency in managing unbalanced datasets and noisy pictures.

Zhentao Hu et al. (2024) [30]suggested a multi-scale fusion architecture utilizing the EfficientNetV2 model to improve skin lesion categorization from dermoscopic images. This methodology integrates superficial and profound characteristics to tackle issues like inter-class resemblance and intra-class diversity. The research utilizes techniques such as class weighting, label smoothing, and resampling to address class imbalance and examines the influence of hair characteristics and lesion areas on classification efficacy. The model attained significant accuracies of 94.0% and 89.8% utilizing the HAM10000 and ISIC2019 datasets, respectively, with AUC values reaching 99.3%. The results illustrate the model's exceptional performance relative to leading approaches, highlighting its efficacy and resilience in skin cancer diagnosis.

Omneya Attallah (2024) [31]Introduced an explainable AI-driven CAD system named Skin-CAD for the identification of skin cancer. The model employs dual-layer characteristics derived from several CNNs (Inception, Xception, ResNet-50, and ResNet-101) to categorize dermoscopic pictures as benign or malignant, and subsequently into seven skin cancer subtypes. Utilizing dimensionality reduction (PCA) and feature selection techniques (mRMR and Relief-F), the system diminishes computational complexity, improves diagnostic accuracy, and alleviates overfitting. Skin-CAD utilizes LIME to deliver interpretable forecasts, mitigating the opacity inherent in conventional CNN models. Validated on benchmark datasets (HAM10000 and Skin Cancer: Malignant vs. Benign), the model attained peak accuracies of 96.5% and 97.2%, respectively, underscoring its promise as a dependable instrument for dermatologists in accurate and rapid skin cancer detection.

Iqra Ahmad et al. (2024) [32]provided a comprehensive methodology for skin lesion segmentation and classification utilizing DeepLabv3+ and Vision Transformer (ViT) models. The DeepLabv3+ model, intended for segmentation, attained remarkable accuracy between 98.9% and 100% on datasets including ISIC-16, ISIC-17, ISIC-18, and PH2. The ViT model far surpassed conventional CNNs in classification, with accuracies of 100% on PH2 and HAM10000, 97.73% on ISIC-19, and 96.97% on ISIC-20. The suggested models tackle issues such as uneven lesion borders, inadequate contrast, and class imbalance by utilizing the self-attention processes of transformers and integrating multi-scale features. This technology has enhanced efficacy relative to current techniques, positioning it as a valuable instrument for precise skin cancer identification.

Dibaloke Chanda et al. (2024) [33]Introduced DCENSnet, an innovative deep convolutional ensemble network for the classification of skin cancer. The model integrates three proprietary Deep Convolutional Neural Networks (DCNNs) with differing dropout layers to enhance the bias-variance tradeoff. DCENSnet, trained on the HAM10000 dataset, employs data augmentation and pixel normalization, resulting in a balanced and resilient feature extraction procedure. The model attained a mean test accuracy of 99.53%, exhibiting elevated precision, recall, F1 score, and AUC metrics across seven categories of skin lesions. The results substantially surpass current state-of-the-art techniques while decreasing computing complexity, illustrating the efficacy of ensemble structures for prompt and precise skin cancer diagnosis.

Joy Christy A. et al. (2024) [34]Devised an innovative CNN framework for skin disease classification that utilizes an Adaptive Percentage Filter for Binarization (APFB) to eliminate hairline noise from skin images and the fast-marching inpainting technique to improve image quality. The HAM10000 dataset, consisting of 10,015 dermoscopic pictures, was utilized to classify seven categories of skin lesions, with 100% accuracy in testing. The APFB approach surpassed traditional hairline noise reduction strategies (CLAHE and Bilateral filtering) on picture quality criteria such as PSNR (47.068), SSIM (0.998), and BRISQUE (13.505). The processed photos were utilized using a custom-designed CNN model including four convolutional layers and two dense layers for classification purposes. This research highlights the need of efficient preprocessing, especially noise elimination, for attaining reliable and precise skin condition detection.

Nirupama and Virupakshappa (2024)[35] Proposed an improved MobileNet-V2-based model for skin disease categorization by using advanced elements such as Squeeze-and-Excitation (SE) blocks, Atrous Spatial Pyramid Pooling (ASPP), and Channel Attention Mechanism. The model was trained on four distinct datasets (PH2, HAM10000, DermNet, and ISIC), attaining an overall classification accuracy of 98.6%. Significant additions encompass multi-scale feature aggregation and enhanced interpretability via attention heatmaps, augmenting the model's capacity to discern complex patterns in dermoscopic pictures. The findings demonstrate the model's resilience, generalizability, and practical use in clinical environments, exceeding current leading approaches while preserving computing efficiency.

D. Nagadevi et al. (2024)[36] Introduced an advanced hybrid convolutional ensemble learning model (AHC-EL) for the identification and classification of cutaneous lesions. The methodology employs a dilated Mask RCNN augmented with an attention mechanism for segmentation and integrates other classification networks, including Residual Attention Network (RAN), MobileNet, and Inception. The authors developed a hybrid optimization method that combines Fitness-aided Battle Royale and Red Deer Algorithms (FBR-RDA) to enhance model parameters. The system was assessed utilizing the HAM10000 (10,015 pictures) and PH2 (200 images) datasets, achieving a classification accuracy of 97.33% on PH2 and 94.19% on HAM10000. This model possesses robust segmentation and classification capabilities, offering a viable method for the early and accurate detection of skin cancer.

Eman M. Elmeslimany et al. (2024)[37] Implemented DualSRA-Net is an advanced dual encoder-decoder network specifically developed for medical image segmentation, with a focus on skin lesion segmentation. The design incorporates advanced components such as atrous spatial pyramid pooling (ASPP), squeeze-and-excitation (S&E) blocks, residual blocks, and attention mechanisms to enhance segmentation accuracy. Assessed across eight datasets, including ISIC-2017 and ISIC-2018, DualSRA-Net achieved outstanding performance metrics, surpassing established architectures such as U-Net and ResUNet++. The model use ASPP to gather multi-scale information while maintaining resolution and leverages attention processes to focus on critical areas of images. DualSRA-Net displayed improved F1 scores, IoU, and Dice coefficients on ISIC datasets, indicating its robustness and effectiveness for various medical image segmentation tasks.

Aniket Patil et al. (2024)[38] Examined cutting-edge data augmentation methods in skin lesion diagnostics to mitigate the lack of annotated datasets in deep learning applications. The study emphasizes conventional approaches such rotation, flipping, scaling, and noise injection, in conjunction with sophisticated techniques such as Test Time Augmentation (TTA), Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Synthetic Minority Oversampling Techniques (SMOTE). The authors underscore the need of integrating augmentation with domain-specific issues, like class imbalance and skin lesion variability, to enhance model robustness and generalization. The study examines adaptive augmentation strategies that utilize model feedback, privacy-preserving data production, and cross-domain augmentation techniques. The investigation highlights the efficacy of augmentation in improving the performance of CNN-based models for skin cancer diagnosis, hence increasing their reliability and generalizability in clinical environments.

Snowber Mushtaq and Omkar Singh (2024) [39]Introduced an innovative ensemble model for multi-class skin cancer classification utilizing the VGG16 architecture. The study included a hair removal preprocessing phase, improving the model's capacity to evaluate dermoscopic pictures efficiently. The ensemble model included outputs from three VGG16 sub-models with distinct random initializations, attaining an accuracy of 89% and an F1 score of 88% on the HAM10000 dataset subsequent to the use of the hair removal approach. The model identified seven categories of skin lesions and exhibited enhanced performance relative to standalone VGG16 models, achieving an accuracy of 88% without hair removal. The findings indicate that integrating ensemble learning with hair removal preprocessing markedly improves classification efficacy, positioning it as a valuable resource for dermatological diagnosis and medical education.

Khalid M. Hosny et al. (2024) [40]Developed a novel deep intrinsic learning approach for multi-class skin lesion classification. The technology alleviates visual impairments and degradation by employing several convolutional filters and intrinsic learning techniques to enhance information transfer. The system utilizes Explainable AI (XAI) methodologies, such as occlusion sensitivity and feature visualization, to guarantee both local and global interpretability of the model's decisions. The proposed model, assessed with the HAM10000 dataset of 10,015 images, achieved an accuracy of 92.89%, a specificity of 95.57%, and a precision of 76.85%. The intrinsic learning approach improves the recognition and classification of seven lesion types, making the model more resilient to mistakes and suitable for clinical use. This study emphasizes the integration of explainable artificial intelligence (XAI) to promote trust and improve the adoption of AI models in dermatological diagnostics.

Anurodh Kumar et al. (2024)[41] Proposed a novel method for multiclass skin lesion classification by combining hand-crafted spatial, cepstral, and spectrogram-domain data with a 1-D multiheaded convolutional neural network (CNN). This mixed-domain strategy mitigates the limitations of existing methods that rely exclusively on spatial data. The proposed approach combines geographical and spectral data to capture essential information necessary for accurate classification. The model, assessed using the HAM10000 and DermNet datasets, achieved accuracies of 89.71% and 88.57%, respectively, exceeding current methodologies. Data augmentation was employed to address class imbalance and improve generalization. The model demonstrated robust performance with little overfitting, making it a viable tool for automated skin cancer diagnosis.

Table 1 provides a comparison of the datasets, model architectures, and performance metrics used by the various recent works that study skin disease classification. This demonstrates the performance of different techniques in deep learning and machine learning, including CNNs, Vision Transformers, and ensemble models. It also illustrates the influence of sample size, preparation methods, and optimization strategies on classification performance. This review should help you to know the advantages and disadvantages of various methods for automatically classifying skin diseases.

Table 1: A comparison of machine learning models for identifying skin diseases.

Ref.	Author and Year	Dataset	Data Volume	Performance	Model
[23]	Vatsala Anand et al., 2022	HAM10000	10,015 images	Accuracy: 90% (ResNet50, ResNet18); Accuracy: 89% (DenseNet121)	DenseNet121, ResNet50, VGG16, ResNet18 with the SGD Optimizer
[24]	Ignatious K. Pious et al., 2022	Custom Dataset	3,500 images	CNN: 97.61%, ViT: 84.31%, SVM: 83.48%, VGG16: 82.49%, ResNet50: 50.05%	CNN, ViT, SVM, VGG16, ResNet50
[25]	Karthik Ra et al., 2022	Merged datasets (e.g., DermNet NZ, Derm7Pt)	4,930 images (expanded to 17,329)	Accuracy: 84.7%	Eff2Net (EfficientNetV2 with ECA blocks)
[26]	V. Auxilia Osvin Nancy et al., 2023	ISIC Archive	Various datasets from ISIC archive	ML: RF 87.32% (with augmentation); DL: MobileNetV2 97.58%, Ensemble of DenseNet and InceptionV3 97.50%, Customized CNN 98.02%	RF, MobileNetV2, Ensemble (DenseNet + InceptionV3), Customized CNN
[27]	Gurpreet Singh et al., 2023	Custom Dataset	44,000 images	Accuracy: 90.1%, Precision: 0.867, Recall: 0.942, F1: 0.891	Fine-tuned VGG16 Model
[10]	NandaKiran Velaga et al., 2023	HAM10000	10,015 images	Accuracy: 95.6% (Test), 95.5% (Validation)	Random Forest, SVM, KNN, Ridge, Decision Tree
[28]	Syed Inthiyaz et al., 2023	Xiangya-Derm	150,223 images	Accuracy: 87.42%	CNN with Softmax Classifier
[29]	Gurpreet Singh et al., 2023	Kaggle	44,000 images	Accuracy: 90.1%, Precision: 0.867, Recall: 0.942, F1: 0.891	Fine-tuned VGG16 Model
[2]	Sarvachan Verma et al., 2024	HAM10000, PH2, ISIC, DermNet	Various datasets (e.g., HAM10000: 10,015 images)	Not specified (review study)	Review of ResNet, VGG16, DenseNet, Transfer Learning, Ensemble Methods
[30]	Zhentao Hu et al., 2024	HAM10000, ISIC2019	HAM10000: 10,015 images;	HAM10000: ACC 94.0%,	EfficientNetV2 with Multi-scale Fusion

			ISIC2019: 25,331 images	AUC 99.3%; ISIC2019: ACC 89.8%	
[31]	Omneya Attallah, 2024	HAM10000, Skin Cancer: Malignant vs. Benign	HAM10000: 10,015 images, Skin Cancer: 3,297 images	HAM10000: 96.5% accuracy; Skin Cancer: 97.2% accuracy	Skin-CAD (Ensemble of Inception, Xception, ResNet-50, ResNet-101 with PCA and LIME)
[32]	Iqra Ahmad et al., 2024	ISIC-16, ISIC-17, ISIC-18, PH2, HAM10000, ISIC-19, ISIC-20	Varying sizes across datasets (e.g., PH2: 200 images, HAM10000: 10,015 images)	Segmentation: 98.9%–100%; Classification: 96.97%–100%	DeepLabv3+ for segmentation; Vision Transformer for classification
[33]	Dibaloke Chanda et al., 2024	HAM10000	10,015 images	Accuracy: 99.53%, Precision: 97.3%, Recall: 96.9%, F1: 96.9%	DCENSnet (Ensemble of 3 DCNNs with dropout variations)
[34]	Joy Christy A. et al., 2024	HAM10000	10,015 images	Accuracy: 100%	APFB for preprocessing + Custom CNN (4 convolutional, 2 dense layers)
[35]	Nirupama and Virupakshappa, 2024	PH2, HAM10000, DermNet, ISIC	PH2: 200, HAM10000: 10,015, DermNet: 19,559, ISIC: 2,357	Accuracy: 98.6%	MobileNet-V2 with SE, ASPP, and Channel Attention Mechanism
[36]	D. Nagadevi et al., 2024	HAM10000, PH2	HAM10000: 10,015 images, PH2: 200 images	Accuracy: 94.19% (HAM10000), 97.33% (PH2)	Hybrid Convolution-Based Ensemble (AHC-EL with FBR-RDA)
[37]	Eman M. Elmeslimany et al., 2024	ISIC-2017, ISIC-2018	ISIC-2017: 2000 images; ISIC-2018: 2594 images	ISIC-2018: F1 92.7%, Precision 95.3%	DualSRA-Net with ASPP, S&E, Residual Blocks, and Attention
[38]	Aniket Patil et al., 2024	HAM10000, ISIC-2017, ISIC-2018	Various datasets	Improved generalization through data augmentation	Various augmentation methods (GANs, VAEs, TTA, SMOTE)
[39]	Snowber Mushtaq et al., 2024	HAM10000	10,015 images	Accuracy: 89%, F1: 88%	Ensemble VGG16 with hair removal
[40]	Khalid M. Hosny et al., 2024	HAM10000	10,015 images	Accuracy: 92.89%, Specificity: 95.57%, Precision: 76.85%	Inherent Deep Learning Model with XAI (Occlusion Sensitivity, Feature Visualization)
[41]	Anurodh Kumar et al., 2024	HAM10000, DermNet	HAM10000: 10,500 images; DermNet: 19,500 images	HAM10000: 89.71%, DermNet: 88.57%	1-D Multiheaded CNN with Mixed-Domain Features

VII. Discussion

The table below provide a comprehensive comparison of various machine learning and deep learning employed for skin diseases detection. The next section takes a look at each column independently to highlight the key findings from these studies.

Various datasets, both public and private, were used by different studies for training and testing their models. **HAM10000** was the most commonly used collection, appearing in numerous studies due to its diverse collection of dermoscopic images. The models performance w.r.t generalisability accordingly given evaluated on other data sets like **ISIC-2017, ISIC-2018, PH2, DermNet and Xiangya-Derm**. Some studies included custom datasets, often sourced from either within a hospital or the internet, to increase diversity in training.

The datasets of different studies varied widely in size. Some research studied small datasets like **PH2 (200 images)** and **ISIC subsets**, which can cause difficulty in generalization. Some used **larger datasets**, such as **HAM10000 (10,015 images)** and **Xiangya-Derm (150,223 images**), to further improve the stability of the model. Other studies that increased the amount of data in their training sets included **Eff2Net**, which went from **4,930 to 17,329 images**. Larger datasets typically resulted in better-performing models that could generalize.

Various architectures were experimented with including traditional **CNN architectures (VGG16, ResNet50, DenseNet121), Vision Transformers (ViT)** and **ensemble learning methods**. Several works investigated the customized design (e.g., **Eff2Net, Skin-CAD, and DCENSnet)** to improve the classification and feature extraction performance. Hybrid models consist of many built-in algorithms. showed group learning works (e.g., **MobileNetV2 + DenseNet + InceptionV3 came strong)** through.

Depending on the dataset size, preprocessing, and model architecture, the classification performance differed among the studies. **CNNs outperformed traditional machine learning methods**, achieving **90% to 99.53%** accuracy. **Joy Christy et al**. achieved the highest accuracy (100%) by preprocessing **APFB with a custom CNN**. On ISIC datasets, **DeepLabv3+ (for segmentation)** also achieved near approach perfect performance as on the same datasets, Vision Transformer (for classification); **DCENSnet** and **Skin-CAD**, ensemble models integrated here, also demonstrated high accuracy and high recall, which suggests that multiple architectures can complement each other. For example, **ResNet50 (50.05%)** had a lower accuracy in some cases compared to traditional Ensemble learning methods, since that it says everything about a dataset and optimization methods.

The landscape of **deep learning for skin disease detection** is fluid, as illustrated by this table that highlights how rapidly the field has shifted, and how dataset selection, model design, and preprocessing are critical to efficiency. Predictors of Interest **CNNs and ensemble models** got it right, while **Vision Transformers and hybrid approaches** seemed promising. Moving forward, the researchers should aim to enhance model extension by employing **larger and more diverse data sets, sophisticated feature extraction approaches**, and explainable artificial intelligence techniques aimed at boosting endorsement in real-world scenarios.

VIII. Conclusion

This study highlights how machine learning can enhance the precision, effectiveness, and accessibility of skin cancer detection. Through the use of deep learning models like Vision Transformers (ViTs) and Convolutional Neural Networks (CNNs), it illustrates the benefits of AI-driven diagnostic systems over traditional techniques. The comparative evaluation of various machine learning models, datasets (HAM10000, ISIC, PH2), and preprocessing methods provides valuable insights into the strengths and limitations of current approaches. Additionally, this study advances the scientific community by assessing new AI methodologies and offering guidance on dataset preprocessing and model optimization. By addressing challenges such as classification accuracy, scalability, and clinical integration, it fosters interdisciplinary collaboration between medical practitioners, data scientists, and AI researchers. These findings not only refine existing diagnostic frameworks but also open the door to more affordable and efficient AI-powered medical solutions. Despite its contributions, this study acknowledges challenges such as dataset limitations, computational costs, and privacy concerns. To ensure the ethical and effective application of AI-based skin cancer detection, future research should focus on privacy-preserving AI techniques, federated learning, and real-world clinical trials. Further advancements in hybrid learning models and explainable AI (XAI) could improve the interpretability and reliability of diagnostic systems. Ultimately, this study lays the groundwork for future advancements in dermatological AI applications, with the potential to enhance early detection, improve patient outcomes, and expand accessibility through the integration of AI-driven diagnostics in clinical workflows and telemedicine. Our findings indicate that CNN-based models, such as ResNet and EfficientNet, perform well in feature extraction and classification, whereas ViTs exhibit superior accuracy in complex lesion differentiation due to their self-attention mechanism. However, ViTs require higher computational resources, which may hinder real-world deployment in resource-limited settings. Additionally, data augmentation and preprocessing techniques significantly impact model performance, helping to mitigate class imbalance issues and improve generalizability.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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