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Advances in Skin Lesion Classification and Nodule Detection: A Review of Deep Learning and Machine Learning Models

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Abstract: Recent advancements in computer vision, machine learning, and deep learning have stimulated anintensifiedconcern for developing effective approaches for the early detection and treatment of dermatological illnesses involving skin lesions. This review paper aims to provide a comprehensive overview of state-of-the-art techniques for detecting, segmenting, and classifying skin lesions, which are crucial for timely intervention and improved patient outcomes. By examining into the challenges associated with physical inspection, the review underscores the importance of leveraging automated methods for skin lesion analysis in healthcare settings.The primary objective of this review is to accurately identify and classify various types of skin lesions, utilizing a range of image formats such as dermoscopic and macroscopic images. By critically examining recent research articles focused on skin lesion classification, the survey puts light on the several methods employed in various publications, with a particular importance on the role of deep learning techniques. Deep learning, a subset of machine learning, has emerged as a powerful tool in this domain due to its proficiency to automatically learn hierarchical representations from data, leading to improved implementation in complicated tasks such as image classification.This survey highlights the benefits and drawbacks of different machine learning and deep learning approaches for skin lesion classification. By integrating and assessing the latest research findings, it aims to provide visions into the current state of the subject and identify areas for further improvement. The integration of machine learning and deep learning techniques in dermatology holds immense capability for enhancing diagnostic accuracy, facilitating early detection, and ultimately improving patient care. Therefore, this survey acts as a valuable resource for researchers, clinicians, and healthcare professionals seeking to use cutting-edge technologies for skin lesion analysis and diagnosis.

Keywords: Skin lesions, Computer vision, Machine learning, Classification, Segmentation, Deep Learning, Dermoscopy, Skin Cancer, Nodules

1. Introduction

Skin lesions refer to areas on the skin that look different from the surrounding skin. They can arise from injuries or damage like severe sunburns, and they may also indicate underlying conditions such as infections or autoimmune diseases. Most skin lesions, including moles and nodules, are noncancerous (benign) and harmless. However, they can sometimes signal more serious health issues. For instance, if a mole changes in shape or color, it's important to have it examined by a doctor to rule out any potential skin cancer[29]. Like moles, nodules can also be benign or noncancerous in most cases. However, they can sometimes indicate more serious conditions, such as certain types of skin cancer or inflammatory skin conditions like dermatitis or acne nodules. It's essential to monitor any changes in nodules, such as rapid growth or changes in texture, and seek medical attention if there are concerns about their appearance or behavior. In addition to the types of nodules mentioned previously, there is also a specific type known as rheumatoid nodules. These nodules are associated with rheumatoid arthritis, an autoimmune condition affecting the joints. Rheumatoid nodules typically develop around pressure points or joints and can vary in size and texture. While they are usually noncancerous, they can cause discomfort and affect mobility. It's important for individuals with rheumatoid arthritis to monitor these nodules for any changes and to discuss any concerns with their healthcare provider[28]. Early and accurate diagnosis of skin lesions, especially the detection of nodules indicative of malignancy, is crucial for effective treatment and improved patient outcomes. In recent years, the integration of deep learning (DL) and machine learning (ML) techniques has revolutionized the field of dermatology by providing powerful tools for automated skin lesion classification and nodule detection.

Skin lesions are of different types that include

Acne

Acne commonly occurs on areas such as the face, neck, shoulders, chest, and upper back. Breakouts manifest as blackheads, whiteheads, pimples, or deep, painful cysts and nodules. It is important to seek appropriate treatment to prevent these adverse outcomes. Figure 1 shows skin lesion of type Acne on the face.



Fig.1. Acne on face[41] **Fig. 2. Cold Sores[41]** **Fig.3.Actinic keratosis[41]**

A cold sore is a painful, red blister filled with fluid that typically emerges near the lips. The herpes simplex viruses, HSV-1 and HSV-2, are responsible for both oral and genital lesions. Prior to the appearance of a cold sore, the affected area often experiences tingling or burning sensations. These blisters can occur singly or in groups, and before they form a crust, they may release a clear yellow fluid. Recurrence of cold sores may be triggered by stress, menstruation, illness, or exposure to sunlight. Cold sores are shown in figure 2.

Actinic keratosis: Actinic keratosis presents as a thick, scaly, or crusty patch of skin, typically smaller than 2 centimetres, resembling the size of a pencil eraser. Found predominantly on sun-exposed areas such as the hands, arms, face, scalp, and neck, it commonly displays a pink hue but may also exhibit a base color of brown, tan, or grey which is shown in figure 3.




Fig.4 Shingles Fig. 5. Epidermoid cysts Fig.6 (a)Nodule on neck Fig.6 (b)Nodule on shoulder




Fig.7. Hives **Fig 8. Keloids** **Fig.9. Warts** **Fig.10 Rash**

Fig.11 (a) Rheumatoid nodules; (b) leg ulcer due to pyodermagangrenosum; (c) erythematous nodule of sweets syndrome over face; (d) cutaneous small vessel vasculitis; (e) erythema nodosum[8].

- **Shingles:** Shingles is a painful rash with blisters that happens when a virus called varicella-zoster becomes active again in the body. This virus is the same one that causes chickenpox. [41]. Figure 4 shows shingles.

- **Epidermoid cysts:**are harmless little lumps under the skin. They can show up anywhere on your body, but you usually find them on your face, neck, or trunk[41].Epidermoid cysts are shown in figure 5.

- **Nodule** : A nodule is a small to medium-sized growth that might be filled with tissue, fluid, or both. It's often larger than a pimple and can feel like a firm, smooth bump under the skin. Usually, it's not a problem, but it might feel uncomfortable if it pushes against other parts of your body. Sometimes, nodules can be deep inside your body where you can't notice them[41]. Figure 6(a) shows nodule on the neck and figure 6(b) shows nodule on the shoulder.

- **Hives :** Hives are itchy, raised bumps that appear when you come into contact with something you're allergic to. They're red, warm, and a bit sore when you touch them. Hives can be small and round, like rings, or they can be big and have a random shape[41]. Hives are shown in figure 7.

- **Keloids**:A keloid is a bumpy or tough spot on the skin that might hurt or make you want to scratch it. It can be the color of your flesh, pink, or red. These symptoms happen where your skin got hurt before[41].Keloids can be seen in figure 8.

- **Warts :** A wart is a bumpy, rough spot that might show up on the skin or inside the mouth or nose. It happens because of certain types of a virus called human papillomavirus (HPV). Warts can spread to other people because they're contagious. Figure 9 shows a wart.

- **Rash:** A rash is when the skin looks or feels different than usual. Lots of things can cause a rash, like bug bites, allergies, certain medications, fungal or bacterial infections, diseases a person can catch from others, or problems with the immune system. [41]. Figure 10 shows a rash.

In figure 11(a) the rheumatoid nodules are visible on the fingers. Figure 11(b) shows leg ulcer due to pyodermagangrenosum. Erythematous nodule of sweets syndrome over face are shown in figure 11(c). Cutaneous small vessel vasculitis on the elbow is shown in figure 11(d). Erythema nodosum on the legs is shown in figure 11(e) [8].

1.2 Scope and Objectives

Harnessing machine support for cancer identification and classification marks a pivotal shift in early-stage research, alleviating manual burdens. This study delves into the realm of skin cancer detection and classification, scrutinizing diverse methodologies.

2. Skin Lesion Identification and Classification System

A computer-aided diagnostic system undergoes several crucial phases, aimed at refining the accuracy and effectiveness of skin cancer recognition and classification:

2.1. Preprocessing:

Preprocessing plays a pivotal role in refining image quality and removing unwanted artifacts that may hinder system performance. This phase employs various techniques:

In [4] the authors proposed image pre-processing pipeline, the initial step involves organizing the dataset by sorting each image within folders according to the seven different diseases present. This sorting is based on parameters like 'Image id' and 'dx' to ensure systematic arrangement[4].

In [2] the researchers have used the Discrete wavelet transforms and convolutional networks for pre-processing.The experiments were conducted on the public Mednode dataset.Two 2D family wavelets and LL, HH bands were used to generate sub images. Discrete wavelet transforms and convolutional networks were used for skin lesion classification.Two 2D family wavelets and LL, HH bands were used for preprocessing[2].

In [3] the authors of the work used mixup, presizing, and test-time augmentation as pre-processing techniques. The models were trained end-to-end, without the need for handcrafted feature extraction.

The preprocessing methods used in Hasan et.al.[5] include segmentation, transfer learning, and augmentation. These techniques are employed to enhance the performance of the hybrid convolutional neural network (CNN) model for skin lesion classification[5].

2.1.1. Morphological Operations:

To address artifacts in skin lesion images, a range of morphological operations is implemented, leveraging mathematical morphology for shape and structure delineation.

Khan et al. [18] proposed a method to enhance dermoscopic images by removing hair and artifacts using black-hat morphological processing and total variation inpainting technique[18].

Salma et al. employed morphological filtering for hair removal and artifacts removal in their automated Computer Aided Diagnosis (CAD) system for skin lesion classification[19].

2.1.2. Colorspace Conversion:

Colorspace conversion enhances image quality by harnessing specific functions tailored to skin lesion recognition, including CIELAB, HSV, and grayscale conversions.

In [3] Fifty different features were extracted based on edge, color, and texture features. Then the Dermoscopic images were transformed into multiple color models for analysis.

In [4] Pre-processing is done with certain processes in the proposed scheme.

The pre-processed images are segmented via the Otsu Thresholding model.

2.1.3. Filtering and Other Enhancement Methods:

Noise and artifacts are mitigated through noise removal algorithms, while image enhancement techniques such as anisotropic diffusion, median filtering, and contrast enhancement bolster image quality for subsequent analysis.

Preprocessing methods used in the paper "Double AMIS-ensemble deep learning for skin cancer classification" by Kanchana Sethanan et al. include data augmentation and fine-tuning of deep learning models. Conditional Generative Adversarial Network (CGAN) techniques are used to create dermoscopic images with a realistic appearance. The augmented dataset is then used to improve the performance of pre-trained deep models, such as VGG16, ResNet50, and ResNet101, on the skin cancer classification task . The authors also create an ensemble of finely tuned transfer learning models, trained on both balanced and unbalanced datasets, to make predictions about the data [6].

2.2. Segmentation:

Segmentation is a pivotal step that divides images into smaller, discernible parts, facilitating lesion localization and classification:

2.2.1. Traditional Segmentation:

Researchers propose diverse traditional segmentation frameworks, employing techniques such as hierarchical k-means clustering, histogram-based clustering with genetic algorithms, and region-growing segmentation for precise lesion delineation.

In [4]Pre-processing is done with certain processes in the proposed scheme. The pre-processed images are segmented via the Otsu Thresholding model.

2.2.2. Traditional Machine Learning Classifiers

In the field of skin cancer identification, machine learning works quite well. For instance, researchers used a Support Vector Machine (SVM) to detect melanoma skin cancer using the ISIC dataset and achieved an accuracy of 96.9%[40]. They also tried different classifiers like SVM, K-Nearest Neighbors (KNN), Ensemble methods, and Decision Trees for melanoma detection, with accuracies of 100%, 87.5%, 87.5%, and 75.0%, respectively[39]. Another study used a decision tree-based Random Forest classifier on the ISIC 2017 and HAM 10,000 datasets and achieved an accuracy of 97% in classifying skin lesions[38]. For dermoscopic classification, researchers used the Naïve Bayes classifier with the Dermatology Information System and DermQuest, obtaining an accuracy of 98.8%[37]. They also experimented with SVM, KNN, Ensemble classifiers, and variants of Artificial Neural Network (ANN), with SVM variants showing the highest accuracy of 83%[36]. In distinguishing melanoma, keratosis, and benign lesions, Naïve Bayes achieved accuracies of 91.2%, 92.9%, and 94.3%, respectively[35]. Additionally, a system based on fuzzy decision ontology was developed for melanoma recognition, using a KNN classifier on DermQuest and Dermatology Information System, achieving an accuracy of 92%[34]. Another system was designed for melanoma recognition using ANN and SVM classifiers, achieving accuracies of 96.2% and 97%, respectively[33].

In [21] Vakili et al. focused on primary skin lesion classification and used a deep learning approach with pre-trained deep convolutional neural network models

3. Related Work

In research paper[10] proposed by Sreena et.al, a multi-stage process involving lesion segmentation, preprocessing, dermoscopic feature extraction, and disease classification was employed. The combination of K-Means clustering, thresholding, Sobel operator, median filter, GLCM, LBP features, and SVM classifier is utilized to enhance the accuracy and efficiency of melanoma detection. The system is evaluated on the ISIC Archive dataset, achieving an impressive 90% accuracy[10].

In [16] Amin et.al 2020, employed a multi-phase approach for the accurate and efficient detection of melanoma, the common fatal type of skin cancer. In the preprocessing phase, images are resized and converted to the Lab color space. Subsequently, Biorthogonal 2-D wavelet transform and the Otsu algorithm are applied for skin lesion segmentation. Deep features are extracted from pre-trained models, AlexNet and VGG16, and serially fused, followed by Principal Component Analysis (PCA) for optimal feature selection. The method utilizes a merged dataset from PH2, ISBI 2016-2017, demonstrating improved accuracy in skin lesion classification[16].

In [17] Damian et.al 2020 proposed a Computer-Aided Detection (CAD) system for detecting and classifying dangerous skin lesions, specifically melanoma, through a fusion of handcrafted features based on the ABCD rule (Asymmetry, Borders, Colors, Dermatoscopic Structures) and deep learning features utilizing Mutual Information (MI) measures. This system, tested on the ISIC 2018 dataset, shows improved performance in terms of accuracy, specificity, and sensibility compared to other state-of-the-art methods[17].

In 2022[1] Shetty et al. in their research for the classification of pigmented skin lesions used both traditional machine learning algorithms and Convolutional Neural Networks (CNN). For machine learning, Decision Tree, Random Forest, SVM, KNN, Logistic Regression, Gaussian Naïve Bayes, and Linear Discriminant Analysis are applied[1].

Choudhary et. al [7] in 2022 presented a comprehensive approach to the challenging task of skin lesion classification, aiming to address the limitations of previous methods. It introduced a four-phase methodology involving image processing, lesion segmentation, feature extraction, and deep neural network (DNN)-based classification.The incorporation of a DNN with the Levenberg Marquardt generalization method for classification, trained on the ISIC 2017 dataset, resulted in a commendable accuracy of 84.45%[7].

In the research paper Nayak et.al[8],proposed valuable insights into the dermatological manifestations of rheumatoid arthritis (RA) in the Eastern Indian population, contributing to a better understanding of the clinicodemographic profile in this specific ethnic and geographic context. The observational cross-sectional design allows for the comprehensive documentation of cutaneous features in RA patients, with a focus on specific, nonspecific, and therapy-related manifestations[8].

The research work[5] carried outby Hassan et.al. in 2022,presents an automated Skin Lesion Classification (SLC) framework named Dermoscopic Expert (DermoExpert), designed to address the challenges posed by the variability in textures, colors, and shapes of skin lesions. The proposed framework utilizes a hybrid Convolutional Neural Network (hybrid-CNN) with three distinct feature extractor modules, enhancing depth feature maps for improved lesion classification. Pre-processing involves lesion segmentation, augmentation, and class rebalancing techniques. Transfer learning from pre-trained models is leveraged, and the deployed DermoExpert's weights are intended for use in a web application. The evaluation on ISIC-2016, ISIC-2017, and ISIC-2018 datasets demonstrates significant improvements in terms of the area under the receiver operating characteristic curve (AUC), surpassing the state-of-the-art by margins of 10.0% and 2.0% for ISIC-2016 and ISIC-2017 datasets, respectively. Though a nodule is one of the forms of lesion the study does not specifically classify the lesions into nodule[5].

In [9] Kumaran et. al proposed a skin lesion detection and classification (SLDC) system using a broad learning system (BLS) with an incremental learning algorithm, named BLSNet. The study focuses on improving the efficiency of deep learning (DL) structures, addressing the time-consuming nature of DL models with large numbers of associated factors in filters and layers. Experiments conducted on ISIC 2019 and PH2 datasets demonstrate that the proposed SLDC using BLSNet outperforms existing DL-based SLDC models, achieving an accuracy of 99.09% and an F1-score of 98.73%. Additionally, the overall execution time of BLSNet is reported to be 0.93 s, showcasing its superiority over conventional approaches[9].

In the research work [12], Varma et. al introduced SLDCNet, a novel approach for skin lesion detection and classification (SLDC) using a hybrid preprocessing-based transfer learning modelemployed for the classification of eight skin lesions. The extensive simulations demonstrate impressive results, showcasing a remarkable classification accuracy of 99.92%, sensitivity of 99%, and specificity of 99.36%. The findings suggest that SLDCNet outperforms existing SLDC approaches, including the standard ISIC-2019 public challenge. The research was not performed on different datasets[12].

In the research work[13] Muhaba et.al, 2022, proposed an automated system for diagnosing five common skin diseases using a pre-trained MobileNet-V2 deep learning model. Clinical images, captured with various smartphone cameras, and patient information collected during registration form the dataset. The proposed system demonstrates a multiclass classification accuracy of 97.5%, along with high sensitivity and precision (97.7%) for the five common skin diseases[13].

In [11] Sharma et al, 2023, in their research paper presented a comprehensive study on skin lesion classification using 14 distinct models, with a focus on the HAM10000 dataset encompassing seven lesion classes. The authors employ various pre-trained models, including EfficientNets, Resnet50, InceptionV3, MobileNetV2, Densenet201, VGG16, VGG19, InceptionResnetv2, Xception, and EfficientNetB0 to B5. Notably, their proposed EfficientNet models surpass traditional pre-trained models like ResNets and VGG16 in terms of accuracy, precision, recall, and validation loss, achieving accuracy above 90% for all EfficientNet models. The paper's strengths lie in its comprehensive evaluation of multiple models and the demonstration of EfficientNets' superiority, but it could benefit by addressing dataset imbalances[11].

The research work [14] , discusses various methodologies for skin cancer detection, with a particular focus on automated systems using deep learning, machine learning, and computer vision. It mentions the utilization of a pre-trained MobileNet-V2 model for diagnosing five common skin diseases. Data for the model are collected from clinical images captured with different smartphone cameras, coupled with patient information obtained during registration. The system is designed achieving a multiclass classification accuracy of 97.5%, sensitivity of 97.7%, and precision of 97.7% for the five common skin diseases. The study could benefit from addressing these challenges and providing insights into the interpretability of the deep learning model[14].

In the research work[15], the authors proposed a skin cancer classification system using a custom Convolutional Neural Network (CNN) applied to the HAM10000 database, enhanced by an Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) for improved image resolution. The ESRGAN pre-processing technique successfully addresses the limitations of Super-Resolution Generative Adversarial Network (SRGAN), leading to better feature extraction. The custom CNN achieves competitive accuracy metrics (98.77% for protocol-I, 98.36% for protocol-II, and 98.89% for protocol-III), outperforming existing models[15].

In 2023, the research work [23] presents a significant contribution to the field of skin cancer classification by proposing a Skin Cancer Classification System (SC-CS) aimed at distinguishing various skin cancer types, including melanoma, vascular lesions, melanocytic nevus, cutaneous fibromas, benign keratosis, and different carcinomas and skin moles. The computational framework and results encompass four separate tests. The first experiment determines the optimal model by detecting nine types of skin cancer using an aggregate dataset (HAM-MB-13312). The second experiment compares the recommended model to existing methodologies using datasets from previous publications (HAM10000 and malignant vs. benign dataset). The third experiment employs a dataset from HAM-MB-13312 that divides all images into two categories

The research work[22] presents a novel framework for skin lesion recognition with a focus on improving accuracy while reducing computational costs. Two pretrained deep learning models, namely Xception and ShuffleNet, are fine-tuned and trained using transfer learning. The deep feature extraction involves the use of a global average pooling layer for both models, and a fusion process is applied to enhance feature representation. To optimize computational time, an improved Butterfly Optimization Algorithm (BOA) is introduced for feature selection and classification using machine learning classifiers such as Support Vector Machines (SVM) and Neural Networks

(NN).The experiments utilize two publicly available datasets, HAM10000 and ISIC2018, to assess the performance of the framework[22].

In [24] the authors aimed to improve skin lesion classification using a weighted average ensemble model combining five deep neural network models. They trained and evaluated the models on 18,730 dermoscopy images from the HAM10000 and ISIC 2019 datasets, applying class balancing, noise removal, and data augmentation techniques. Results showed significant performance improvement, with macro-average recall scores ranging from 84% to 91% for individual models and up to 94% for the weighted average ensemble[24].

In the study{27] the researchers introduced a novel bilinear CNN approach for accurately classifying seven skin lesion classes with high precision and low computational cost. The proposed framework incorporates data augmentation, transfer learning, and fine-tuning techniques to enhance classification performance over the HAM10000 dataset. Results demonstrate a significant improvement in accuracy compared to the state-of-the-art, with the bilinear approach achieving an average accuracy of 0.9321[27].

In the research work [25], the researchers introduced an approach to automatically diagnose skin diseases using deep learning methodologies like deep feature extraction from Resnet50, VGG16, and Deeplabv3. Utilizing Hybrid Squirrel Butterfly Search Optimization (HSBSO) for feature transformation and Modified Long Short-Term Memory (MLSTM) networks for classification enhances the accuracy of skin disease classification[25].

In the study [26] the researchers developed a model for accurately classifying seven types of skin lesions, crucial for early diagnosis of skin cancer, leveraging features extracted from convolutional neural networks (CNN) and the ABCD rule, a standard clinical guideline. Evaluation on the HAM10000 dataset reveals the Cosine Similarity Classifier achieves the highest accuracy of 96.4% when combining CNN-based features with those from the ABCD rule[26].

In [28] Uma et al proposed a method for detecting and classifying Rheumatoid Nodules (RN) using deep learning models, specifically dual three-dimensional Deep Convolutional Networks (DCNN) for detection and an improved Residual Network (Res-Net) for classification. The research work focuses on identifying and classifying rheumatoid nodules present on the skin, determining whether they are benign or malignant.The paper introduces the use of skip connections in the Residual Network (Res-Net) for training, which improves the learning process by allowing the network to skip training from certain levels and link directly to the resultant outcome[28].

Mubeen et al.[29] reviewed the analysis of a number of metaheuristic techniques in , assessing their effectiveness in classifying skin lesions and predicting the likelihood of different types of skin cancer. These techniques included Hybrid Whale Optimisation (HWO), Bat Algorithm (BA), Artificial Bee Colony (ABC), Ant Colony Optimisation (ACO), and Firefly Optimisation. Insights to improve the early identification and diagnosis of skin disorders were gained by closely examining the operations and results of these algorithms, which has significant positive effects on healthcare and society at large[29].

For the automatic classification of skin lesions, Rasool et al. introduced a unique method in [30] known as Bootstrapping Ensembles and Convolutional Neural Networks (BE-CNN). With an accuracy rate of 92.67% on average, the study outperforms previous methods on the ISIC-HAM 10000 datasets. This enhancement is due to the model's better ability to categorise skin lesions into the appropriate stages when compared to traditional approaches based on conditions and stages. The outcomes demonstrate how BE-CNN can improve automated skin cancer detection by handling segmentation and classification tasks at the same time[30].

In their work, Shaik et al. [31] covered a variety of Machine Learning (ML) approaches for diagnosing and identifying diseases as well as the numerous difficulties associated with using AI and ML to healthcare. There is also discussion of other issues pertaining to maintaining patient data privacy[31].

In the article[42] the author has taken an example of a patient who had lesions on the skin and later developed nodules and cysts which led to patient’s death as it was ignored by the patient[42].

The authors in [43] suggested a convolutional neural network model for categorising skin conditions based on model fusion. The model's capacity to extract features is improved by integrating deep and shallow features, merging models, and adding an attention module. Experiments show that our suggested model outperforms baseline models DenseNet201 and ConvNeXt_L by 4.42% and 3.66%, respectively, using our proprietary dataset that is mainly composed of skin conditions that resemble acne. The suggested model outperforms previous state-of-the-art models, achieving an accuracy of 95.29% and a f1-score of 89.99% on the publicly available HAM10000 dataset[43].

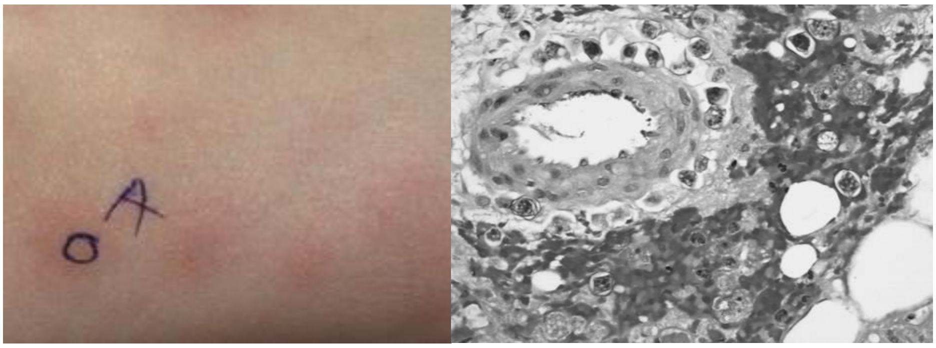

Fig.11 (a). Skin lesions [42] **Fig.11(b) internal condition of lesion[42]**

In their study, Imthiyaz et al. [44] introduced a deep learning framework designed to automatically classify skin cancers. Their model, trained on the Xiangya-Derm dataset comprising 150,223 images, utilized a pre-trained convolutional neural network (CNN). In their study, Imthiyaz et al. [44] introduced a deep learning framework designed to automatically classify skin cancers. Their model, trained on the Xiangya-Derm dataset comprising 150,223 images, utilized a pre-trained convolutional neural network (CNN)[44].

Table1. Comparison of Metrics of various approaches

Research Paper	Algorithm/Approach	Data Set	Accuracy	Precision	F1 Score	Recall	AUC
[1]	CNN	HAM10000	94%	88%	86%	85	---
[3]	1-D Convolutional Layer Model	ISIC-2017 ISIC-2018	88%	--	---	---	----
[5]	Hybrid CNN	ISIC - 2016 ISIC - 2017 ISIC-2018	----	----	----	----	0.96 0.95 0.97
[6]	VGG -16	ISIC	92%	-----	------	---	-----
	ResNet50		92%				
	ResNet101		92.25%				
[7]	DNN with the Levenberg Marquardt	ISIC - 2017	84.45%	----	-----	-----	----
[9]	BLS-Net	ISIC-2019	99.09%		98.73%.	-----	----
[10]	K-Means Clustering &	ISIC	90%	-----	-----	-----	------

	Thresholding, GLCM, LBP						
[11]	EfficientNetB0, EfficientNetB1, EfficientNetB2, EfficientNetB3, EfficientNetB4 EfficientNetB5	ImageNe t Datasets	90%	-----	-----	-----	------
[12]	FrCN	ISIC-2019	99.92%	-----	-----	99%	------
[13]	Mobilenet-v2 model		97.5%	97.7%	------	97.7%	-----
[15]	CCNN	HAM100 0	98.77%	-----	-----	-----	------
[16]	AlexNet&VGG 16	PH2, ISBI 2016-2017 combine d					
[17]	MobileNetV2	ISIC 2018	92.4%	92.08%	89.16%	------	89.64 %
[18]	CNN	ISIC	96%	-----	-----	------	------
[19]	VGG-16, ResNet50, ResNetX, InceptionV3, MobileNet	ISIC 2017 HAM100 00 ISIC 2017 ISIC 2017 ISIC 2017	96.70% 95.91% 92.68% 87.58% 83.99%	93.53% 94.81% 90.89% 85.89% 84.68%	93.54% 93.64% 90.99% 87.36% 84.98%	------- ------- ------- ------- -------	92.84 % 92.97 % 92.69 % 87.34 % 84.98 %
[20]	DenseNet201	ISIC 2018	77%	------	-----	------	--------

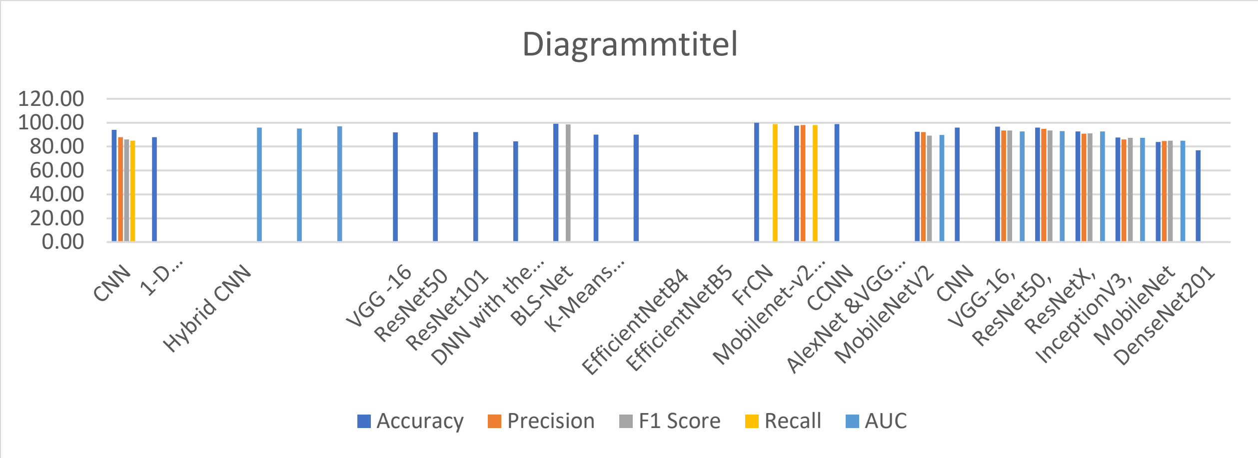

Fig.12. Comparison of Metrics of various Approaches

4. Results

The results of different research papers have been analysed in this work and Table1. shows the comparison of different metrics when different approaches were applied. In figure 12. a graphical representation of comparison of various metrics applied on different algorithms is shown. It is observed that CNN shows better performance among other algorithms.

5. Conclusion

This review paper discusses how deep learning is transforming dermatology in amazing ways. Doctors can use these methods to more correctly diagnose skin ailments, including cancer, allowing patients to receive better treatment. These computer models can assist clinicians in providing second opinions or determining what to do next, so improving patient care. Overall, this analysis demonstrates how deep learning is improving dermatology, and with additional research and collaboration between deep learningexperts and dermatologists, greater progress in identifying and treating skin problems is expected.

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