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Machine Learning and Convolutional Neural Network used to skin lesion classification - A review

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***Abstract*—In the proposed review there have been collected the state-of-the-art papers that treat skin lesions, computer vision methods used for image processing, and AI algorithms used to classify the features extracted from lesions and images for the last five years. The study started with a PRISMA analysis performed on Google Scholar with the keywords "medical image analysis" AND "melanocyte detection" AND "skin epidermis" AND "deep learning classification" and Open Alex with the keywords "medical image analysis" AND "melanocyte detection" AND "skin epidermis" AND "deep learning classification." After a rigorous selection, only 30 papers were included in the present study. An important particularity of this study is a highlighting of the AI-used algorithm, the features extracted from images, the dataset implied in the study, and the obtained accuracy. Also, a classification of the occurrence of AI algorithms in the studies is shown in a representative graph.**

***Keywords*—skin lesions, AI algorithm, deep learning**

I. Introduction

More than 3,000 skin diseases have been documented, encompassing both acute and chronic conditions that can affect individuals across all ages and social backgrounds [1].

The data provided by the European Academy of Dermatology and Venereology[1] shows that 43% of the EU citizens experienced at least one skin disease within the past 12 months. The most prevalent skin conditions reported among those surveyed include fungal skin infections, atopic dermatitis (eczema), alopecia, and acne. A recent statistic performed by American Cancer Society[2] (ACS) estimates for melanoma in the United States (US) for 2025 to be as follows: approximately 104,960 new cases of melanoma will be diagnosed, including about 60,550 in men and 44,410 in women. Other statistics all done in US provided by Skin Cancer Fundation[3] show that 1 in 5 Americans will develop skin cancer by the age of 70, and more than 2 people die of skin cancer every hour.

The traditional diagnostic framework known as the ABCDE rule serves as a basis for assessing the characteristics of lesions through visual examination with dermoscopes, This method emphasizes the importance of evaluating the Asymmetry, Border, Color, Diameter, and Evolving nature of skin lesions to identify potential melanomas. By systematically applying the ABCDE criteria, clinicians can enhance their diagnostic accuracy and improve patient outcomes [2].

Given the possibility of dividing skin cancer into several subcategories, the field of artificial intelligence (AI) has been adapted for dermatological entailment by involving machine learning (ML) and convolutional neural networks (CNN). Taking into account the dynamic of the AI field and the concerning statistic previously mentioned, this review was proposed for corroborating the important skin lesion diseases and important AI algorithms used in their monitoring and classification. Moreover, the present article aims at emphasizing the progress of AI methods that amplify the accuracy in diagnosing skin lesions as well as the challenges of its clinical implementation. By analyzing various algorithms and their effectiveness, we hope to provide a comprehensive overview that can be of guidance for further research and applications in dermatology.

II. Literature review

Convolutional neural networks (CNN), as part of deep learning (DL), offer remarkable resolutions in image segmentation and skin lesion classification. Also DL, especially CNN, offers promising solutions in skin cancer diagnosis, and hybrid approaches could lead to more robust

[1] https://eadv.org/advocacy/bosd-supplement/

[2] https://www.cancer.org/cancer/types/melanoma-skin-cancer/about/key-statistics.html

[3] https://www.skincancer.org/skin-cancer-information/skin-cancer-facts/

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diagnostic tools for dermatology. The aim of this section is to provide an overview of the current state of research in the field of deep learning in terms of the progress made in the diagnosis, treatment and prognosis of skin lesions in the last 5 years. For a detailed selection of the papers, the collocation “skin melanoma” and features were searched in the title of the papers.

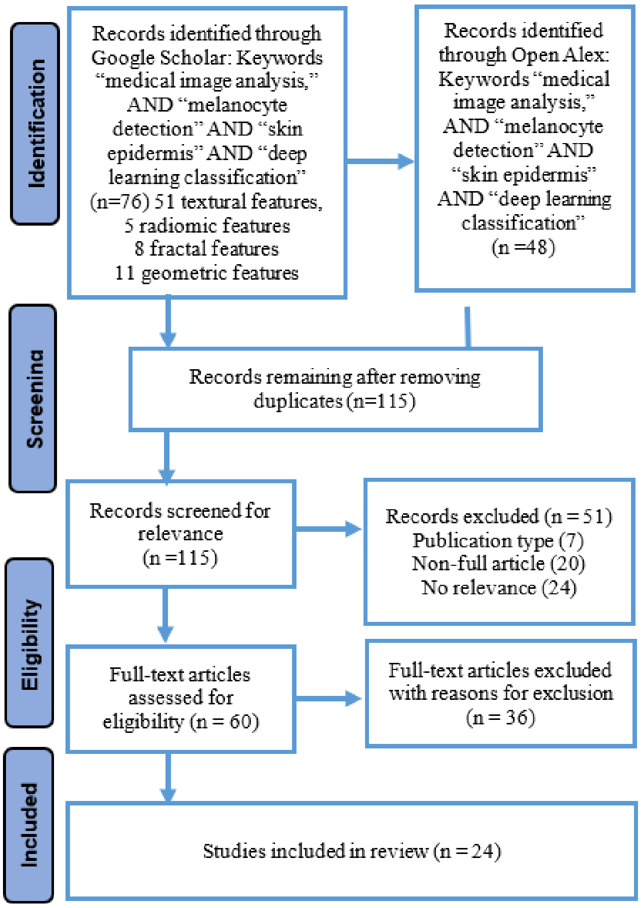

Fig. 1. PRISMA flow diagram skin lesion

For credibility, the cited papers were not regarded as reliable solely because of their index and recentness. Priority was accorded to publications published in peer-reviewed journals or established conferences and those by authors with a reliable publication record in dermatology image analysis, medical imaging, computer vision, or machine learning. As an exception, when a paper presented an unusually high performance, the dataset origin, split strategy, validation protocol, availability of external validation, and agreement with the authors’ prior results were considered before accepting it as evidence. This screening process is significant as rapid reviews can exaggerate performance when isolated papers with limited methodological transparency are included.

Vidya et al. [3] proposed algorithm applies feature extraction using ABCD rule, Gray Level Co-Occurrence Matrix (GLCM) and Histogram of Oriented Gradients (HOG) feature extraction for early detection of skin lesion. Segmentation was performed using Geodesic Active Contour (GAC) which segments the lesion part separately, thus being further useful for feature extraction. Starting from machine learning techniques such as SVM, KNN and NB, they classified skin lesions between benign and melanoma with an accuracy of 97.80%.

Tumpa and Kabir [4] perform hair removal from preprocessing of dermatoscopic images with the Maximum Gradient Intensity algorithm, while for separation of skin lesions from images they use the Otsu Thresholding algorithm. The proposed method includes much more information about image features, such as ABCD, GLCM and LBP.

Moldovanu et al. [5-7] and Tabacaru et al. [8] proposed a classification system for geometric, fractal, and morpho-granulometry features extracted from dermatoscopic images. Prior to analysis, images underwent preprocessing using the Dull-Razor method to remove hair, followed by segmentation using computer vision techniques to focus solely on the region of interest. The classification process employed various methods, including the k-nearest neighbor (kNN) classifier, radial basis function neural network, feedforward backpropagation network, random forest (RF), support vector machines (SVM), AdaBoost, decision trees (DT), Gaussian Naïve Bayes (NB), and extreme gradient boosting.

Keerthana et al. [9] presents a skin cancer classification model using the 26-layer U-net architecture for image segmentation and the DenseNet architecture for classification, achieving an accuracy of 85.50%. Ragab [10] introduces a novel way of classifying lesions. Hair filters, gel, bubbles, and specular reflection are all options. An improved leveling method is presented that is used in an innovative method for detecting and removing cancerous hairs. Feature classification using this method resulted in an accuracy of 94.40%.

Ragumadhavan et al. [11] use a novel approach based on wavelet transform for feature extraction, followed by local ternary model analysis. After preprocessing the image with a weighted median filter, segmentation is investigated using a series of common techniques, the best result being generated by combining the hydrographic transform with the fusion of maximum similarity regions. The intersection of the histograms, Bhattacharya distance, Chi-square distance and Pearson correlation coefficients are calculated. The U-net architecture is used for segmentation.

Tabacaru et al. [12] implemented an algorithm for processing dermatoscopic images. The study predicts the spread of melanoma by creating a mask surrounding the melanoma. The proposed algorithm analyzes the region of interest (ROI) using the normalized two-dimensional cross-correlation (NCC) method and predicts the pattern in the peritumoral area that most closely resembles the texture of the melanoma. An eight-step algorithm was developed to predict the skin area surrounding the lesion.

Kashikar et al. [13] compared two deep learning models, a classic CNN model together with a ResNet-50 as the basis and a Faster R-CNN model combined with MobileNetv3 as the basis to improve the way melanoma detection is done. The modified CNN based on ResNet-50 had an accuracy rate of 85.06%, which recommends it for accurately classifying melanoma lesions. The integrated approach proposed by the researchers produced an overall accuracy of over 90%.

Ornek et al. [14] investigated the effectiveness of artificial intelligence and machine learning techniques in achieving accurate classification of skin cancers by adapting four machine learning algorithms to perform classification tasks. The accuracy rates obtained by Artificial Neural Network (ANN), KNN, RF and LR, ranged from 67.20% to 71.80%.

Thepade et al. [15] presents a pioneering approach by which they tested the effectiveness of pre-trained deep convolutional neural network (DCNN) models, especially ResNet50, when merged with Thepade sorted block truncation coding (Thepade SBTC) for melanoma detection. They combine the features extracted from these models with Thepade SBTC 10-ary features to enhance the discernment abilities of the machine learning classifiers.

Hussien and Alasadi [16] present a deep learning method for melanoma classification, for the detection of a type of skin cancer. They develop a convolutional neural network model that includes 27 thin layers, specifically designed to extract features from images of skin lesions and categorize them into melanoma and non-melanoma groups. To evaluate the impact of each layer on the efficiency of the model, ablation analyses were performed, and the accuracy of the developed system reached 99.99%.

Saleh et al. [17] adjusted four other distinct models: AlexNet, InceptionV3, MobileNet and ResNet50 to extract features that would allow skin cancer classification, but used the Grey Wolf Optimizer Algorithm to extract only the essential features. For the classification of dermoscopic images into distinct classes, 51 models based on six pre-trained ML classifiers were developed. For AlexNet, Inception V3 and ResNet 50, the algorithms were trained for a cubic SVM, a quadratic SVM, a large neural network and a medium neural network, while for MobileNet V2, the linear SVM and ensemble subspace discriminant models were trained separately. The AlexNet algorithm with a classic GWO produced the optimal model, with a classification accuracy of 94.50%.

Kadia and Patel [18] combined manual and automatic feature extraction of various machine learning techniques such as neural network, convolutional neural network and K-Nearest Neighbor to identify, classify and represent melanoma using the principal component analysis algorithm. The model classified melanoma skin lesion, trained and evaluated skin specific lesion, lesion sensitivity, skin sensitivity, lesion.

Naeem et al. [19] implemented a deep learning algorithm for skin cancer detection called DVFNet. To detect skin cancer, dermoscopic images are enhanced by preprocessing using anisotropic diffusion methods to remove artifacts and noise in order to improve image quality. Researchers used a hybrid data preprocessing technique for unbalanced datasets, creating new synthetic samples for the minority class with Synthetic Minority Over-sampling Technique (SMOTE) and with Tomek Links removing pairs of samples that are the nearest neighbors, improving their separation. Starting from a model based on the VGG19 and HOG architectures, their approach allows improving the performance of machine learning models in skin cancer prediction tasks by creating a more balanced dataset, derived from the ISIC 2019 dataset. The DVFNet algorithm achieves an accuracy of 98.32%.

Shakya et al. [20] use three pre-trained and fine-tuned networks: VGG19, ResNet18 and MobileNet approaches for skin cancer image classification and use four machine learning classifiers: SVM, DT, NB and KNN, for feature extraction. All these algorithms are trained using segmented images which are obtained using the active contour approach. Before segmentation, a preprocessing step involving scaling, denoising and image enhancement is performed. Following the analysis of parameters such as the number of images, the number of epochs and the learning rate, it was observed that the pre-trained networks ResNet18 and MobileNet together with the SVM classifier achieve the best result - 92.87%

Naseri and Safaei [21] used deep learning models such as DenseNet in combination with deep convolutional neural networks (DCNN) to analyze medical images and diagnose diseases. They found that these models outperformed conventional methods such as SVM, KNN, or RF in correctly identifying the disease in more than 95% of cases.

Manikandan et al. [22] developed an efficient deep learning classifier (EDLCS) for the classification of dermatoscopic images. The researchers investigated three different color spaces, such as red-green-blue (RGB), hue-saturation-brightness (HIS), and LAB. The RGB dermatoscopic images are first converted to HSV and LAB spaces to investigate the HSV and LAB color spaces for melanoma classification. The resulting image after color space conversion is fed into the proposed EDLCS to evaluate its performance.

Jayasree et al. in [23] proposed an efficient method for image segmentation and dermoscopic detection of skin lesions to solve the problem of melanoma classification. The proposed algorithm aims to eliminate false negative diagnoses that can lead to erroneous data, as well as false positive screenings that are resource-consuming. After the segmentation stage, the researchers, when using Fixed-Grid Wavelet Network (FGWN), approached deep learning techniques to observe whether the type of skin lesion is cancerous or not. Starting from an efficient Wavelet network, the features of the segmented images were extracted using the orthogonal least squares method. After training the ResNet-50 and AlexNet models for a period of at least 100 epochs, the segmentation indicated an accuracy of 99.78% and for the detection of skin cancer lesions, the CNNs achieved an accuracy of 93.37%.

TABLE 1 COMPARATIVE ANALYSIS WITH STATE-OF-THE-ART WORK IN SKIN CANCER

Ref.	Year	Extracted Features	Dataset and accuracy	Acc.	Methods and AI Technologies
[3]	2020	Textural features	ISIC dataset images of melanoma	97.80%	SVM, KNN and NB classifier
[4]	2021	Textural features	PH2 dataset	97.70%	ABCD, GLCM și LBP
[5]	2021	Fractal Dimension	7-Point Med-Node PH2,	95.42% 94.71% 94.88%	kNN classifier, Radial basis function neural network
[6]	2021	Geometric features	7-Point, PH2, MED-NODE	96.70%	Feedforward Back Propagation Network
[7]	2023	Geometric features	MED-NODE 7-Point PAD-UFES-20.	95.50% 95.60% 98.60%	RF, SVM, AB KNN, DT, Gaussian NB and three neural

					networks.
[8]	2024	Morpho-granulometry features	PH2	92.30%	RF, extreme gradient boosting
[9]	2022	Textural features	ISBI 2016 dataset	85.50%	U-Net with 26 layers DenseNet
[10]	2022	Textural features	Melanoma Skin Cancer Dataset	94,40%	CNNs
[11]	2022	Textural features	PH2 dataset	98,60%	SVM, Bayesian classification, DT, KNN
[12]	2023	Textural features	7-Point, PH2 dataset	95.10%	NCC, and SSIM
[13]	2024	Textural features	ISIC 2019	90.00%	Faster R-CNN ResNet50
[14]	2024	Textural features	ISIC 2019 Skin Lesion dataset	71,80%	ANN, KNN, RF, LR
[15]	2024	Textural features	HAM10000 dataset	92,78%	RF, IBK și NBTree
[16]	2024	Textural features	Kaggle skin-cancer dataset	99.99%	Deep Neural Network
[17]	2024	Textural features	ISIC 2017 dataset	94.50%	AlexNet, InceptionV3, MobileNet și ResNet, SVM
[18]	2024	Geometric features	ISIC dataset ISBI dataset	87.42% 91.10%	KNN, VGG
[19]	2024	Textural features	ISIC 2019 dataset	98.32%	Analysis of variance (ANOVA)
[20]	2025	Textural features	ISIC 2018 dataset	92.87%	SVM, DT, NB, KNN
[21]	2025	Textural features	HAM10000 dataset	95.00%	DenseNet and DCNN
[22]	2025	Textural features	PH2 database from University of Porto	99.58%	Efficient deep learning classification (EDLCS)
[23]	2025	Textural features	ISIC 2019	87.00%	Fixed-Grid Wavelet Network (FGWN)

III. CASE STUDY: ISIC/HAM10000 DERMOSCOPIC LESION CLASSIFICATION

For a focused case study, the ISIC/HAM10000 setting was selected because it is public, widely used, and sufficiently heterogeneous to support comparison between conventional machine learning and CNN-based approaches. The HAM10000 dataset described by Tschandl et al. [24], contains 10,015 dermoscopic images collected from multiple sources and released for academic machine-learning comparisons through the ISIC archive. The ISIC challenge series described by N. C. F. Codella et al. [25] and collaborators formalized the evaluation of lesion segmentation, attribute detection and disease classification, while also showing that algorithms with similar test-set performance may generalize differently. In the selected papers, the case study can therefore be expressed as the task of classifying dermoscopic lesions into benign/malignant or multi-class diagnostic categories after preprocessing, segmentation, hand-crafted feature extraction, or end-to-end CNN feature learning.

Using this case study, similar approaches can be compared systematically along five dimensions: input data, preprocessing/segmentation, feature representation, classifier, and validation risk. This comparison is more informative than reporting accuracy alone, because the reviewed works use different class balances, train-test splits and dataset combinations.

Hand-crafted image features with classical machine learning: Vidya et al. [3], Tumpa and Kabir [4], Moldovanu et al. [5-7] and Tabacaru et al. [8] rely on preprocessing, lesion segmentation or ROI extraction followed by descriptors such as ABCD, GLCM, HOG, LBP, fractal, geometric and morpho-granulometry features. These approaches are transparent and computationally light, but their performance is sensitive to segmentation quality and manually designed features.

Transfer learning with established CNNs: Kashikar et al. [13], Thepade et al. [15], Shakya et al. [20] and Kim et al. [24] use ResNet, VGG, MobileNet, Inception or DenseNet backbones, either as fine-tuned classifiers or feature extractors combined with SVM, DT, NB or KNN. This family is a strong baseline for ISIC/HAM10000-like data, but it needs careful split control, augmentation and external validation to avoid optimistic performance estimates.

CNNs combined with optimization or feature selection: Saleh et al. [17] and Naeem and Anees [19] reduce redundant features by using Grey Wolf Optimizer, ANOVA-based selection or deep feature fusion. These pipelines can improve accuracy and reduce feature dimensionality, but they add hyperparameter complexity and may overfit if validation is not independent.

Segmentation-first deep models: Keerthana et al. [9] and Jayasree et al. [23] separate lesion localization from classification by using U-Net, wavelet-network segmentation or CNN features extracted from lesion-focused masks. This design is clinically intuitive because the lesion region is isolated, although segmentation errors can propagate into the final diagnosis.

Color-space and domain-specific variants: Manikandan et al. [22] and the ISIC challenge methods by Gessert et al. [26] illustrate the use of HSV/LAB color-space transformations, metadata-aware modeling and ensemble strategies. These methods can be useful for heterogeneous data, provided that metadata leakage and acquisition-source bias are controlled in the experimental protocol.

IV. DISCUSSION AND FUTURE DIRECTIONS

Kim et al. [27] present the method of selecting and tuning basic CNN models taking into account the characteristics of medical data as well as the approaches of using Transfer learning for the task of medical image classification.

We reviewed the latest light models for finding skin cancer. We made a list of different types of studies, looking at and analyzing selected ones in detail. The research looked at problems and improvements in different areas, such as how to use various convolutional neural networks to find skin cancer, how to make programs require fewer resources (time, space, memory), and how to make and analyze images better. We broke the model into smaller pieces to see how well each piece works on its own and how they work together to find skin cancer.

To improve the early detection of skin cancer, researchers should focus on combining different types of data, such as images and text, to create better systems for early diagnosis of skin cancer. They should also use advanced computer models that analyze different types of data together and test their models on different groups of people over time to see how well they perform. Furthermore, they should use semi-supervised learning methods to cope with the problem of not having enough labeled data, using methods such as self-training and data augmentation to make the model better and less dependent on expert-labeled data. They have to compare these models to the old ways of doing things and make sure they work well on different types of data. Moreover, they should use new technologies such as federated learning, explainable artificial intelligence, and light models or light vision transformers to make faster progress in skin cancer research.

Fig. 2 provides an overview of the progress made in skin cancer analysis over the last 5 years.

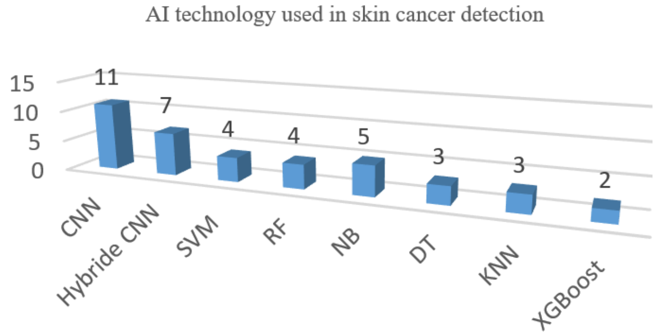

Fig. 2. AI methods and technologies used in research

CONCLUSION

A recurring limitation in the reviewed studies is the dependence on relatively small or imbalanced datasets and the frequent absence of external validation. High resource consumption is another practical limitation, especially for large CNNs and ensemble architectures. Larger, better documented datasets and more efficient algorithms are therefore needed to improve robustness, reproducibility and clinical applicability.

The most widely used pre-trained CNNs are those trained on large datasets containing millions of images. These models are frequently used for Transfer Learning and Fine-Tuning in classification tasks, object detection, semantic segmentation.

While relying on selected papers from 2021-2025, this review of skin cancer research explores recent methods used for disease detection using machine learning and deep learning. The analysis emphasizes techniques for medical-image preprocessing, feature extraction, segmentation and classification, especially pre-trained CNNs and transfer learning. It also notes that GANs, federated learning, explainable artificial intelligence and light vision transformers are increasingly relevant for future diagnostic systems.

Regarding the architectures CNN, models such as ResNet, Inception and EfficientNet have continued to be preferred due to their high performance and computational efficiency. These architectures have demonstrated the ability to handle complex data sets and provide accurate results in various computer vision applications.

The most widely used classification algorithms to assign a label to an image in CNNs in recent years are Softmax for multi-class and Sigmoid for binary classification, but also KNN, SVM and RF combined can provide very good results for certain data sets. On the other hand, for regression problems in CNNs for the prediction of continuous values, such as facial point detection, object position estimation, or image denoising, the most used algorithms are Mean Squared Error (MSE) for standard regression problems and Huber Loss for noisy data.

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