Survey of Detection and Identification of Black Skin Diseases Based on Machine Learning

K. Merveille Santi Zinsou(✉), Idy Diop, Cheikh Talibouya Diop, Alassane Bah, Maodo Ndiaye, and Doudou Sow

Ummisco-Sénégal, Institut de Recherche pour le Développement (IRD-Hann), Ecole Supérieure Polytechnique (ESP/UCAD), Ecole Doctorale des Sciences et des Technologies, University Gaston Berger of Saint Louis (UGB), BP: 234 Saint-Louis, Senegal

{zinsou.kpetchehoue-merveille-santi,cheikh-talibouya.diop}@ugb.edu.sn, idy.diop@esp.sn

https://www.ugb.sn/

Abstract. Due to their physical and psychological effects on patients, skin diseases are a major and worrying problem in societies. Early detection of skin diseases plays an important role in treatment. The process of diagnosis and treatment of skin lesions is related to the skills and experience of the medical specialist. The diagnostic procedure must be precise and timely. Recently, the science of artificial intelligence has been used in the field of diagnosis of skin diseases through the use of learning algorithms and exploiting the vast amount of data available in health centers and hospitals. However, although many solutions are proposed for white skin diseases, they are not suitable for black skin. These algorithms fail to identify the range of skin conditions in black skin effectively. The objective of this study is to show that few researchers are interested in developing algorithms for the diagnosis of skin disease in black patients. This is not the case concerning dermatology on white skin for which there is a multitude of solutions for automatic detection.

Keywords: Black skin diseases · CNN · transfer learning · Deep learning · Machine learning

1 Introduction

Dermatological disorders are one of the most common diseases in the world. Although frequent, their diagnosis is sometimes complicated due to the tone of the skin, its color, the presence of hair, etc. The usual diagnostic process is quite restrictive for patients because it requires significant time and financial resources. A good skin examination is also time-consuming for the doctor because he must examine every lesion on the patient's entire body and use modern and adequate equipment. In Africa, in addition to the profession's difficulties, the

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challenges in this health field are enormous. Indeed, it is estimated that 30% of the Sub-Saharan population suffers from skin diseases [1]. With so many potential patients, there is a severe shortage of qualified personnel to provide better patient care. There is one dermatologist for a workforce ranging from 350,000 to one million people [1]. In light of this observation, deploying AI in the branch appears to be a viable and long-term solution. Deep learning algorithms have recently demonstrated exceptional performance on a variety of tasks, particularly the diagnosis of skin diseases. However, the results from Africa are not as conclusive as those from developed countries. This research critically examines current dermatological algorithms based on artificial intelligence. Following that, we will identify the limitations of existing solutions and potential challenges that will allow researchers to address dermatological issues related to black skin.

2 Skin Diseases

It is vital to have a minimal understanding of the clinical management of skin diseases because many processes such as feature extraction, image preprocessing, image resizing, image segmentation, etc. are based on them. This section discusses the anatomy of the skin, the current skin diseases, and the most recurrent diseases in SENEGAL.

2.1 Anatomy of Skin

The skin is the human body's largest organ (representing 16% [2] of its total weight). It provides many functions such as barrier protection, immune protection, body temperature regulation, UV protection, detection, storage, and vitamin D synthesis. It comprises three main layers: the epidermis, the dermis, and the hypodermis.

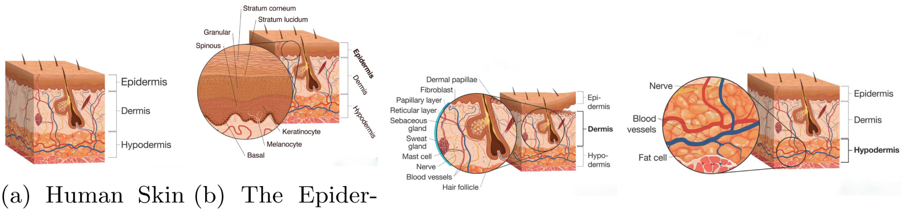
The epidermis forms a semi-permeable barrier and creates our complexion. It is made up of three sorts of cells: keratinocytes (which make the protein keratin) and melanocytes (which make the melanin responsible for skin pigmentation). It is divided into five layers:

- The **basal layer:** is the lower layer of the epidermis. This layer forms keratinocytes and melanocytes (responsible for protecting the skin from the sun's rays).
- **The spinous layer:** is located above the basal layer. It gives a spiny appearance and contains the keratinocytes that have come up from the basal layer.
- **The granular layer:** is found above the spinous layer and contains keratinocytes that produce fats that form a barrier to prevent dehydration by retaining water inside the skin.
- **The lucent layer:** is located above the granular layer, present only on the palms of the hands and soles of the feet, and contains keratinocytes that are brought up from the granular layer.
- **The stratum corneum:** this is the most superficial layer of the epidermis. Here, the keratinocytes die, flatten out, and are now called corneocytes.

The **dermis** is a connective tissue, which supports the epidermis, protects the vascular network and the nerve fibres. The dermis is composed of two layers.

– **The papillary layer** is a thin layer containing wavy projections that curve up and down at the dermis and the epidermis border.
– The **reticular layer**: is a dense connective tissue composed of a network of elastic fibers.

The deeper subcutaneous tissue (**hypodermis**) consists of connective tissue and fat. The fat protects the body through its cushioning effect, stores energy, and provides insulation for the body (Fig. 1).



(a) Human Skin [2] (b) The Epidermis [2] (c) The dermis [2] (d) The Hypodermis [2]

Fig. 1. Human skin anatomy

Although the anatomy of the skin is universal for every human being, there are some differences in skin color. Differences in skin color between individuals are due to variation in pigmentation, which results from genetics (inherited from biological parents), sun exposure, or both. Below are some of the typological differences [47] (Table 1):

Table 1. Difference between black and white skin [3]

	Black skin	White Skin
Definitions	Black skin refers to the dark coloration of skin due to the production of eumelanin in humans	White skin refers to the light coloration of skin due to the production of pheomelanin in humans
Type of melanin produced	Eumelanin - dark brown to black color	Pheomelanin - red to yellow color
Cell size	Larger cell size with increased diameter	Smaller cell size with decreased diameter
Number of melanocytes	High melanocyte count	Low melanocyte count
Amount of Melanin produced	High	Low
pH	More acidic	Less acidic

- The thickness of the epidermis of black skin is identical to that of white skin, but the stratum corneum has 20 cell layers instead of 16. It is, therefore, more compact and more resistant.
- The skin of black people is relatively less hydrated than that of white people.
- The skin's pH is slightly more acidic (4.8 to 5.2) than white skin's.
- In white skin, melanocytes are small, clustered within the keratinocytes, and degraded in the upper layers of the epidermis. In blacks, melanosomes are twice as large and are dispersed in the cytoplasm of keratin cells. They are not contaminated and arrive intact in the stratum corneum.

2.2 Common Skin Diseases in Senegal

In the context of our study, we work with dermatologists from the National Hospital Center of Senegal:

- Albert Royer Children's Hospital in Dakar is a hospital center whose mission is to provide medical and surgical care to children from 0 to 15 years old;
- Aristide Le Dantec Hospital.

We have identified, with the help of dermatologists, the most recurrent skin diseases in Senegal, as summarised in the table below (Table 2).

Skin diseases manifest differently depending on skin color, age, sex, etc. For example, eczema usually appears as itchy, dry, darker, or red areas of skin. In people with skin color, eczema often appears "ashen," grayish, or brown in color. Considering age, eczema in infants, is usually seen on the cheeks and forehead. Children see it on the wrists, ankles, hands, feet, elbow, and knee creases. In adults, eczema is seen on the neck, face, feet, and back of the hands, upper arms and back, elbow and knee creases, fingers, and toes. Based on the above, it is essential to consider the unique characteristics of black skin in developing an intelligent algorithm for identifying black skin diseases [18].

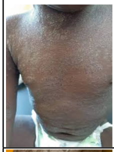
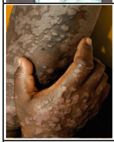
3 State of the Art of Detection and Classification Algorithms for Uncolored Skin Diseases

Deep learning models (architectures) and classical machine learning (ML) methods produced remarkable results in the skin disorders recognition and classification.

3.1 Machine Learning Algorithms

System developed by Nawal Soliman Abdalaziz Alkolifi Alenezi [19] has a 100% accuracy rate for diagnosing three kind of skin illnesses (Eczema, Melanoma, Psoriasis, and Healthyskin). A pre-trained AlexNet model was used to extract features, and a multi-class support vector machine (SVM) classifies the features.

Table 2. Common skin diseases in Senegal

Disease	Description	Disease	Description
	Atopic dermatitis (eczema) causes your skin to become red and itchy. Most common in children, it can occur at any age. It is a chronic condition that flares up from time to time. Asthma or hay fever may accompany it [4].		Contact dermatitis is a skin response that happens when something touches your skin and causes a rash. The rash may begin quickly or develop over time. Contact dermatitis is fairly prevalent; practically everyone gets it at some point [5].
 [48]	Psoriasis is a chronic inflammatory disease that manifests differently in people with varied skin tones. Plaque psoriasis can be red, purple, or grayish on darker skin. [27].	 [6]	Acne is characterized by oily skin and pimples on the face, upper back, and chest. More embarrassing than serious, acne (sometimes called "acne vulgaris") is typically a teenage skin condition that can have significant psychological effects.
 [7]	Dermatophytosis are mycotic infection of the skin and nails caused by various fungi and classified based on their location on the body. They are also referred to as "ringworm" or "superficial fungal infections of the skin.	 [8]	Erysipelas is caused by bacteria, most often streptococcus. It appears on the legs in 85% of cases and on the face in 10% of issues. The bacteria usually enter the skin through a wound. It results in strong reaction in the skin.
 [7]	Scabies is a parasitic skin infection caused by a mite, Sarcoptes scabies. The mites live and lay their eggs under the skin, which results in severe itching, particularly at night. There are two types of scabies, crusted (severe form) and noncrusted. [9].	 [10]	Lupus: purely cutaneous lupus (erythematous lupus) and systemic lupus, an autoimmune disease, affecting primarily young women, with a prolonged coursewhich can potentially affect all organs or tissues [11]. It threatens the life of patients in 5 to 10% of cases [32].
 [12]	Dermatomyositis is a rare and heterogeneous autoimmune pathology characterized by a noninfectious inflammatory disease of the muscles and skin associated with a vasculopathy predominant physiopathological element. It can be very severe, and its complications are numerous.	 [13]	Scleroderma is characterize by chronic hardening and tightening of the skin and connetive tissue, joint pain, and heartburn. A rare disease primarily affects women and usually occurs btween 30 and 50 years. Treatments include medication, physical therapy, and surgery.
 [14]	Necrotizing Fasciitis is a severe bacterial infection that destroys the tissue under the skin. This "flesh-eating" disease occurs when bacteria enter the body through a skin lesion. Possible symptoms include blisters, fever, fatigue, and pain much worse than the appearance of the wound would suggest.	 [15]	Impetigo is a bacterial skin infection caused by staphylococcus or streptococcus. It can be crustymost frequent, or bullous. The bacteria are spread through direct contact with the lesions, which causes small epidemics in children's communities.
 [16]	Pyoderma gangrenosum is a rare form of neutrophilic dermatosis that causes rapidly progressing skin ulceration. The lower extremities are where these uncomfortable ulcers most frequently manifest [38].	 [17]	Mycetoma is a chronic, progressive infection caused by champions or bacteria, which affects the feet, upper limbs, back, head, etc. Late detection of this disease leads to the amputation of the infected limb. It evolves slowly over months or years (10, 15 years), with progressive extension and destruction of muscles, tendons, fascia, and bones.

Thanh-NganLuu et al. [20] provide a framework to categorize human melanoma and non-melanoma skin cancer samples using the Stokes decomposition approach and several artificial intelligence (AI) models. With the proper pre-processing of the input parameters, all models exhibited a classification accuracy (F1 score) of greater than 90%. Overall, the suggested framework presents a potential method for quickly and precisely categorizing tissue samples of human skin cancer.

A novel automated skin melanoma detection system (ASMD) including melanoma index was proposed by Kang HaoCheong et al. in [21]. The DermQuest, DermIS, and ISIC2016 databases were used to compile 600 benign and 600 malignant DD pictures for the proposed ASMD approach. An accuracy over 97.50% was reached when RBF (radial basis function) and SVM (the support vector machine) are used together.

V.R. Balaji et al. [22] proposed a system based on a dynamic graph cut algorithm and Naive Bayes (a probabilistic classifier) respectively for skin lesion segmentation and skin disease classification. This system is fed by the ISIC (International skin imaging collaboration) 2017 dataset. They attained accuracy rates of 91.2% for melanoma, 94.3% for benign cases, and 92.9% for keratosis.

In [23] System developed by Mustafa Qays Hatem and colleagues has achieved 98% accuracy in classifying skin lesions. The K-nearest neighbor (KNN) method is used in the classification process to distinguish between benign lesions that don't indicate pathology and malignant lesions that do. The database consists of 40 images of melanoma and 40 image of normal skin.

Joshua D. B. Mendoza et al. [24] proposed a system is based on Field-programmable gate array (FPGA) and uses an algorithm to recognise seven skin disorders (acne, warts, tinea, psoriasis, eczema, rashes, and hives). The system had a 90% accuracy rate. A total of 40 diseased skin images were identified, including five images for each skin disease.

Rahat Yasir et al. [25] proposed a system that successfully identifies nine skin disorders (eczema, acne, leprosy, psoriasis, scabies, foot ulcer, vitiligo, Tinea Corporis, Pityriasis Rosea) with 90% accuracy. A total of 775 dermoscopic images were collected and validated by a specialized physician. The system works in two phases: preprocessing images and disease's phase classification.

Table 3. Comparison of methods based on classical Machine Learning algorithms.

Topic	Skin diseases	Method	Accuracy	Features extracted	Advantage(A) and Limitation(L)
[19] (2019)	Eczema, Melanoma, Psoriasis, Healthyskin	AlexNet + SVM	100%	**unknown**, use of pre-trained AlexNet model for feature extraction	A: digital image of disease L: 100% accuracy means result of Overfitting
[20] 2022	Melanoma and non-melanoma skin cancer	Stokes-Mueller matrix decomposition + (Random Forest/Decision Tree/SVM/XGBoost/Radius Neighbors/Ridge)	90%	**Efficient optical parameters** Refractive index, Dispersion, Transmittance and Transmission coefficient	A: hybrid framework proposed L: small number images to classify diseases, models with an accuracy of 100% hide an overfitting problem
		Stokes-Mueller matrix decomposition + ExtraTree/k-Nearest Neighbors (k-NN)/Multilayer Perceptron (MLP)	100%		
[21] 2021	Melanoma	BEMD (Bidimensionnel Empirical Mode Decomposition of images) + SVM + RBF	97.50%	texture, entropy features	A: High accuracy L: Dataset images are not captured in the same conditions
[22] 2020	Benign cases, Melanoma, keratosis	Dynamic graph cut algorithm + Naive Bayes	94.3% - 91.2% - 92.9% respectively	Colour and texture features	A: use of digital images, dynamic graph cut method framework for segmentation L: small unbalanced dataset
[23] 2022	Melanoma	K-nearest neighbour (KNN), fast fourier transform	98%	Mean (using fast Fourier transform), standard deviation, histogram-based mean and standard deviation, edge-based pixel count of area and hole, and edge-based logarithmic pixel count of area and hole	A: dermoscopic image L: system is ineffective with a huge dataset and sensitive to the dataset's noise.
[25] 2015	eczema, acne, leprosy, psoriasis, scabies, foot ulcer, vitiligo, Tinea Corporis, Pityriasis Rosea	eight 8 Pre-processing algorithm (grey image, sharpening filter, median filter, smooth filter, binary mask, histogram, YCbCr, and Sobel operator) + forward back propagation artificial neural network	90%	average colour code of infected area, infected area size in case of pixels and shape, edge detection of an infected area, User input:(gender, age, duration, liquid, type, liquid color, elevation, feeling)	A: new approach proposed with acceptable accuracy L: the pre-processing stage is a little complex.

3.2 Deep Learning Algorithms

A. Muhaba and al. [26] proposed an automated deep learning system using the mobilenet-v2 pre-trained model, capable of diagnosing five skin disorders (lichen planus, acne vulgaris, atopic dermatitis, tinea capitis, onychomycosis). Data from clinical pictures and patient information power this learning system. Using various smartphone cameras, 1,088 skin images of the five main conditions were gathered in southwest Ethiopia, eastern Amhara, and the Afar area.

An Eff2Net convolutional neural network (CNN) model was proposed by Karthik R and al. [27]. The Efficient Channel Attention (ECA) block and EfficientNetV2 are the foundations upon which this concept is based. In comparison to other deep learning methods described in the literature, the suggested CNN learned roughly 16M parameters to categorize the disease. The model has a test accuracy of 84.70% overall when applied to the four classes of actinic keratosis (AK), melanoma, psoriasis, and acne.

In [28], the system proposed is fed with 3406 images and can identify seven skin diseases (Psoriasis, acne, Chickenpox, Vitiligo, eczema, Tinea Corporis, and Pityriasis rosea). The dataset is considered unbalanced due to its uneven number of images. An accuracy of 94.4% was reached by applying the oversampling and data augmentation techniques to pre-process input data.

Moolchand Sharma and al. [29] developed a system that can identify and classify five major skin conditions (eczema, viral infections, psoriasis and lichen planus, benign tumors, and fungal infections) with 95% accuracy. They did this by choosing residual neural networks (ResNet) with 50 layers that were given a collection of 1900–2500 photos.

One-to-many approach and convolutional neural networks were combined to develop a system suggested by Kemal Polat and al. [30] for classifying skin diseases from dermoscopic images, which they claim achieves 92.90% accuracy. To build the image dataset, they extracted skin disease images from the HAM10000 dataset.

In [31], 3400 clinical pictures from the ISIC (International Skin Imaging Collaboration) database make up the dataset. The optimal probability-based deep neural network (OP-DNN) is applied to the pre-processed images during the training phase. The resulting prediction model achieved an accuracy of 95%.

A technique that uses the HAM10000 dataset to segment and classify skin lesions for automatic skin cancer diagnosis was proposed by ADEKANMI A. ADEGUN and al. [32]. Using a fully convolutional network (FNC) encoder-decoder, the method involves first learning the intricate and irregular features of skin lesions. Using the DenseNet, which is made up of dense blocks that have been combined and connected using the concatenation strategy and the transition layer, makes up the second component of the strategy. The precision, recall, and AUC score of the suggested model are each 98%, 98.5%, and 100%, respectively.

An intelligent method was created by Saad Albawi and al. [33] that can categorize three different sorts of skin conditions: melanoma, neuroma, and typical conditions. The suggested solution uses pre-processing called adaptive filtering to get rid of extra noisy areas in the skin image. The International Skin Imaging Collaboration (ISIC) database feeds the developed model, which has a 96.768% accuracy rate.

The system developed in [34] can identify 17 skin diseases based on the multi-class classifier: Deep Generative Adversarial Network (DGAN). They gathered a total of 13,650 pictures for the model from four different datasets: PH2, SD-198, Interactive Dermoscopy Atlas, and DermNet. Half of the photos for each category of skin diseases were tagged, and the other half were left unlabeled.

A system based on the pre-trained AlexNet model is proposed in [35]. It is fed by a total of eighteen hundred images collected from the Internet. All classes achieved 100% accuracy except for Pityriasis Versicolor, Tinea, and Seborrheic Dermatitis with 93.3%, 96.7%, and 90% respectively.

R. Bhavani and al. [36] developed a method based on ensembling three machine learning algorithms: Inception v3, MobileNet, and Resnet. Three neural network models are used to forecast and classify the diseases when an input is supplied to the system. The model is 100% accurate in identifying three skin conditions: atopic dermatitis, actinic keratosis basal cell carcinoma, and acne.

Halil Murat unver and al. [37] developed an intelligent system capable of identifying melanomas, using the Yolov3 (You Only Look Once) algorithm for image classification and GrabCut for image segmentation. The method has been tested on two publicly accessible datasets, ISBI 2017 and PH2, which contain a combined 2150 images. The model achieved an accuracy of 93.39% and the data augmentation method was not used.

Table 4. Comparison of deep learning approaches

Topic	Dataset	Skin diseases	Architecture and future extracted	Accuracy	Advantage(A) and Limitation(L)
[26] 2021	1880 image collected in southwestern Ethiopia	acne vulgaris, atopic dermatitis, lichen planus, onychomycosis, tineacapitis	- mobilenet-v2 - 41 features from patiens information (age, gender, anatomical sites (abdomen, anterior torso, armpit, chin, ear, forehead, lateralface, lower back, lower extremity, nail, neck, periorbital region, posterior torso, scalp and upper extremity), symptoms of the diseases, outputs of 1280 images feature maps	**97.5%**	A: Hight level accuracy L: The images collected were not taken under the same conditions. The dataset is not homogeneous.
[27] 2022	undefined	acne, actinic keratosis, melanoma and psoriasis	EfficientNetV2 + Efficient Channel Attention (ECA)	84.70%	A: New detection approach proposed L: Precision under 90%
[28] 2019	3406 images	Acne, eczema, Chickenpox, Pityriasis rosea, Psoriasis, Tinea Corporis, Vitiligo	- MobileNet - colors and shape features	94.4%	A: using oversampling techniques to transform an imbalanced dataset into a balanced dataset
[29] 2021	900–2500 images of each disease type from DERMNET	eczema, psoriasis and benign tumors, lichen planus, fungal infections, and viral infections)	- ResNet	95%	A: High accuracy L: Ten epochs for training are not enough to qualify the model as accurate
[30] 2020	Extract from HAM10000	actinic keratoses and in-traepithelial carcinoma, benign keratosis, basal cell carcinoma, dermatofibroma, melanoma, melanocytic type and vascular lesions	- CNN + one-to-many approach - Without feature extraction	92.90%	A: New detection approach proposed L: Accuracy to be improved
[32] 2020	HAM10000	Actinic keratoses and intraepithelial carcinoma, basal cell carcinoma, benign keratosis-like lesions , dermatofi- broma, melanoma, melanocytic nevi and vascular lesions	- fully convolutional network (FNC) + Conditional Random Field (CRF) + DenseNet	98%	A: The system uses approaches for hyper-parameter optimization to lessen network complexity and boost computing performance
[33] 2019	ISIC database	melanoma, neuroma and atypical diseases	- adaptive region growing technique + two-dimensional discrete wavelet transform (2D-DWT) + CNN - texture and geometric features: (contrast, correlation, energy, homogeneity, gradient, color)	96.768%	A: High accuracy
[34] 2022	13,650 images from various dataset (PH2, SD-198, Interactive Dermoscopy Atlas and DermNet)	acne, vulgaris, angioma, carcinoma, keratosis, nevus, Milk coffee macule, dermatofibroma, eczema, keloid, psoriasis, dermatitis ulcer, steroid acne, versicolor, heat rash, and vulgaris	**-Deep Generative Adversarial Network (DGAN) - 256 differents features maps**	91.1%, and 92.3% for unlabelled and labeled datasets, respectively	A: the algorithm works with labeled and unlabeled images L: Accuracy to be improved
[35] 2021	2070 images collected on the internet	Acne, Atopic Dermatitis, Contact Dermatitis, Human Papilloma Virus Infection, Pityriasis Versicolor, Seborrheic Dermatitis, Tinea, Urticaria, Vitiligo	- AlexNet	97.8%	A: High accuracy L:AI System for Nigerian dermatologists but images are not for black skin disorders

(*continued*)

Table 4. (*continued*)

Topic	Dataset	Skin diseases	Architecture and future extracted	Accuracy	Advantage(A) and Limitation(L)
[36] 2019	13000 images from Dermnet	Acne, Actinic Keratosis Basal Cell Carcinoma, Atopic Dermatitis	- Logistic regression + Ensembling three machine learning algorithms: Inception v3, MobileNet, and Resnet - high-level features (considered entire image), middle-level features (extracted over the region), low-level feature (extracted pixel by pixel features)	100%	A: New approach, High accuracy L: The combined architecture is complex and does not respect the size of the input images for each model
[37] 2019	2150 images from PH2 and ISBI 2017	melanomas	- Yolov3 (You Only Look Once) + GrabCut	93.39%	A: New approach, acceptable accuracy L: The proposed method does not give an accurate segmentation of the lesion because it includes the surrounding border.

Tables 4 and 3 show us that there are multiple approaches to identifying skin diseases from images. Although these systems have achieved high accuracy, they could not correctly identify skin diseases on black skin. It is because black skin has certain key specificities (parameters) unique to black skin that are not considered. These specificities are, among others: the complexion, the number of melanocytes (cells responsible for the production of melanin), the melanin type, the shape and the color taken by the disease on black skin, the PH, and the degree of hydration.

4 State of the Art of Black Skin Disease Detection Algorithms

Scientific research on the automatic detection of skin diseases has accelerated in recent years. Some recent works have proposed techniques for automatically identifying conditions on black skin.

For example, "FIRST DERM" used neural networks to generate Skin Image Search, an AI tool capable of identifying 33 skin diseases with 80% accuracy. They worked on a total of 300,000 photos (black skin images are only about 5–10%) [38]. Ugandan researchers tested this application on 123 other photos to diagnose six forms of black skin diseases. They were only 17% accurate. [39]; This AI's effectiveness in diagnosing black skin diseases yields a low percentage.

Google has introduced a dermatology application called "Derm Assist" that recognizes 288 distinct skin disorders from photos. Initially, the system was trained on a training dataset of 64837 photos of 2399 patients in two states with an accuracy of up to 97%. People with fair skin, deeper white skin, or light brown skin made up 90% of the database. Dermatologists warn that the app may overdiagnose or underdiagnose persons who are not white due to biased sampling. In conclusion, this AI was not designed for people with skin darker [40]. In [41], an auutonomous AI system achieved 68% accuracy in determining the most likely skin lesion morphology. The accuracy increased to 80% when the highest forecast made by the AI system was enlarged to include its three most likely predictions. In contrast, primary care doctors had a diagnosis accuracy of 68% with a visual assistance and 36% without. An extra batch of 222 heterogeneous photos of various Fitzpatrick skin types (I-III or IV-VI) [46] was used to test the AI.

Aggarwal [42] has demonstrated a considerable difference between individuals with fair skin and patients of color in the accuracy of AI for detecting melanoma and basal cell carcinoma (BCC). For this, two image recognition models were tested on 30 photographs after being validated on 38 images and trained on 150 images each. The ratio of melanoma- and BCC-displaying pictures was constant throughout each phase. A model with light skin received training, and another with skin of color. By measuring the area under the receiver operating characteristic curve, the two models' performance was evaluated. For fair skin, the sensitivity was 0.60, while for SOC (system on chip), it was 0.53. The specificity was, respectively, 0.53 and 0.47. The positive and negative predictive values, respectively, were 0.56 and 0.50 and 0.57 and 0.50. F1 values for fair skin were 0.58 and for SOC they were 0.52. The AI SOC model, according to the author, nonetheless produced subpar results compared to the model trained on lighter skin, even when the same number of photos were utilized for training, validation, and testing.

Laila Hayes and al. [43] developed an intelligent system capable of identifying three types of skin diseases (Dermatosis Papulosa Nigra (DNP), Vitiligo, Hyperpigmentation) on black and brown skin via a convolutional neural network (EfficientNet) with transfer learning. The system was trained on 385 images (175 DNP, 160 Vitiligo, 50 Hyperpigmentation) and achieved 94% accuracy.

An analysis of the current shows that dermatological algorithms based on artificial intelligence (AI) and able to identify a range of conditions dermals do not work effectively on black skin. The mixed results obtained during previous studies are related to the fact that scientists do not have suitable datasets on the diseases of black skin and do not take into account some specifics features which are unique for black skin conditions.

5 Discussion and Potential Challenges

This study reviews various machine learning techniques and several architectures for deep learning. **These approaches show a significant change in accuracy, time, and complexity over the years**. The intelligent systems based on these approaches deal with various skin diseases. The proposed methodologies share steps such as image acquisition, image preparation, image segmentation to extract the skin lesion, feature extraction to extract the features, model classification that uses the extracted features and predicts the disease, and model evaluation.

However, as shown in Fig. 2, there are some differences where the machine learning classifier takes the feature vector as input and outputs the object class. In contrast, the deep learning classifier uses the image to determine the object class.

Another difference is noted in the feature extraction stage, which is one of the most critical phases. Feature extraction with machine learning algorithms requires a deep knowledge of the image processing domain since the extraction is done manually. Also, designers have a free hand to choose the features they find meaningful, although this is tedious. On the other hand, with deep learning algorithms (e.g., CNN), the extraction is done automatically, as the algorithm identifies by itself the most suitable intrinsic and discriminating features on images that will constitute the vector characteristic for the classification stage. As the comparative Tables 4 and 3 show, the main features extracted by various approaches are:

- color characteristics (grayscale, red, green, blue)
- texture characteristics (contrast, regularity, asymmetry, uniformity, entropy, gradient, homogeneity, kurtosis)
- geometric characteristics (shape)
- effective optical parameters: refractive index, dispersion, transmission, and transmission coefficient.

In addition, some researchers have used dermoscopic images on the one hand and digital images on the other as input to the model to be trained. **Dermoscopic images** come from a device called a dermatoscope, which is a diagnostic instrument used by a general practitioner or dermatologist during luminescent microscopy examinations of skin lesions. It allows them to see the deeper layers of the skin and identify abnormalities more precisely. The **digital images** come from photo cameras or telephone cameras.

Dermatological images make it difficult to identify skin lesions. It is due to the presence of unwanted or defective elements (artifacts) in the images, the most common of which are: reflections, hairs, oil bubbles, hair, lighting changes, pixelation, different skin types, etc. Some disorders are challenging to recognize because there is little color difference between the backdrop and foreground (the lesion) due to the diversity and characteristics of the many skin types. Therefore, improper image segmentation will prevent the machine learning algorithms from correctly identifying the disease. Additionally, for accurate skin disease diagnosis, machine learning algorithms must be designed to deal with clinical and camera image data.

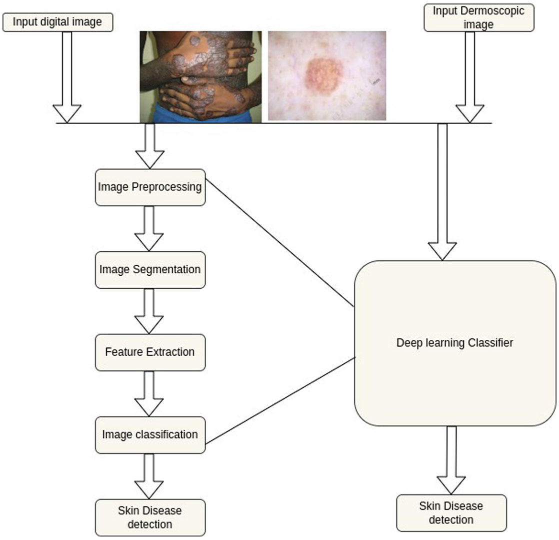


Fig. 2. Deep learning and machine learning methods process

Despite the achievements of these intelligent algorithms, they are ineffective in identifying and diagnosing skin diseases in dark-skinned people, especially those hyperpigmented. The ineffectiveness of these algorithms on black skin can be explained by the fact that in Africa, due to difficulties in accessing care, patients only come to the hospital when the disease is at an advanced stage, which is not the case in Europe, America, and Asia. It reflects that the disease presents a different and more advanced appearance in the images. Consequently, an algorithm trained on images of white skin cannot have the same reactions when subjected to images of black skin, since the algorithm bases most of its knowledge on how skin lesions appear on fair skin. Moreover, there are significant differences between the manifestations of skin diseases in blacks and whites [44,45]. It is means that characteristics such as the shape, colour and colour of the disease on the black skin are not extracted. Added to this is the virtual absence of a representative set of images of dark-skinned people, and the existing algorithms focus mainly on images of light-skinned people. The anatomical difference at the cellular level (Subsect. 2.1), which causes skin color, explains the proposed algorithm's inefficiency in identifying black skin diseases. Skin color (tone) is mainly determined by a pigment called melanin, a substance produced by melanocyte cells. This state of affairs indicates that the skin color (complexion) and the type of melanin were not considered during feature extraction.

Finally, the analysis shows that to develop an intelligent algorithm capable of identifying skin disorders in black skin, scientists need to take into account key parameters which are unique and specific for black skin, such as: skin color(complexion), melanin type, skin color (tone), shape and color taken by diseases in black skin. From all of the above, potential challenges to address are:

- collect, annotate, and label images to have a dataset of black skin images.
- develop a reliable, intelligent algorithm that can identify, classify skin diseases, and can extract characteristics that are unique and specific to black skin diseases;
- Set up a generic framework that allows the easy addition of new diseases.

Subsequently, we will first work on the study and proposal of an intelligent system to assist in the diagnosis of mycetoma. Mycetoma because it is a disease that affects much more of the population of remote areas (farmers, for example) whose early detection is vital to avoid severe cases leading to the imputation of the infected body member.

6 Conclusion

Based on the foregoing, we may conclude that AI is well adapted to identifying skin diseases and that several methodological approaches for reliable identification exist. However, we must admit that the numerous techniques provided for identifying skin diseases are nearly ineffectual when it comes to detecting black skin diseases. It is because specific black skin parameters such as skin color (complexion), melanin type, the PH, the degree of hydration, shape and color taken by disorder on lack skin, are not considered at the feature extraction stage to allow the models to classify skin diseases correctly. Indeed, decades of clinical and scientific research have mostly concentrated on light skin problem, excluding underprivileged people whose symptoms may manifest differently. It is also worth noting that a shortage of medical workers skilled in "black skin dermatology" is a source of daily difficulty for patients in Sub-Saharan Africa, where dermatology illnesses are common. Few patients are properly diagnosed and treated. Inadequate patient management can result in serious problems. At the conclusion of this analysis, it is urgent and critical to address the issue of "black skin" dermatology in order to design an effective dermatological algorithm for reliable identification and detection that will feed highly representative black skin data.

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