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SKIN DISEASE PREDICTION BASED ON MEDICAL IMAGES USING DEEP LEARNING TECHNIQUES: A REVIEW

Divya [1], Ranjna Jain [2] and R. Girija [3]

[1, 2] Department of Computer Science and Technology, Manav Rachna University, Haryana, India
[3] Centre for Health Innovations, School of Engineering and Technology, Manav Rachna International Institute of Research & Studies, Haryana, India

er.divyasoni@gmail.com, ranjnajain@mru.edu.in

Corresponding author: drgirija.set@mriu.edu.in

Abstract. Skin diseases are common these days. Ignoring these diseases can lead to development of skin cancer in the current situation. In recent years, deep learning has evolved as an emerging technique for predicting disease more efficiently in the early stages as compared to other techniques. This greatly benefits from the application of image examination technique which is broadly beneficial to Medical Services. In Dermatology's intricacy and high cost make it challenging to diagnose. Using deep learning dermatoscopic images can be detected at an early stage. Early-stage detection of skin lesions is useful to predict whether the lesion can lead to cancer and then it can be treated before it spreads throughout the different organs of body. The growing incidence of skin conditions worldwide calls for the creation of automated, scalable, and precise diagnostic tools to support primary care physicians and dermatologists.This paper provides a survey on some of the prevalent skin diseases focusing on their symptoms, prediction and accuracy via focusing on recent advancement of using deep learning techniques.The purpose of this study is to provide researchers and clinicians a collective understanding of how deep learning methods can improve diagnostic accuracy, reduce manual workload, and support clinical decision-making in dermatology.

Keywords: Deep learning; Convolutional Neural Networks; Benign; Malignant; Skin cancer (skin disease).

1. INTRODUCTION

Nowadays , skin diseases are very common, such as acne, rashes, rosacea etc. Some skin diseases can lead to skin cancer. Skin diseases can have various negative consequences, such as depression, lack of confidence, embarrassment etc. There are many types of skin diseases, some of which have the same symptoms, so prediction of disease at the initial stage is very important[1].

Deep learning is evolving rapidly and its applications are spread across various areas. In the healthcare industry, it is used for detecting diseases. It has different methods that predict diseases faster and efficiently than humans, such as CNN (Convolutional Neural Networks). It belongs to the subset of Deep Neural Networks that can recognize and categorize specific aspects in images. Their utilization includes NLP, classification of images, and multimedia analysis for medical purposes, and image and video recognition[2-4]. CNNs are highly effective in classifying images because they can automatically learn the spatial hierarchies of features that are critical for identifying objects in photos, such as edges, textures, and forms. It has various activation functions, like sigmoid, relu etc., which activate the neuron when it satisfies the particular condition. Fig. 1 denotes the methodology available for classifying the images for different stages.

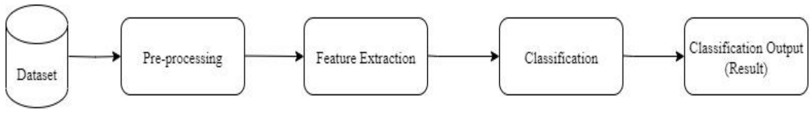

Figure. 1: Methodology for image classification.

Image input — Initially, images are captured and are inserted into the system (dataset) for image processing. It is necessary to offer an adequate image with an appropriate size and resolution to be uploaded to the system. These images may be retrieved from open databases or skin image will be uploaded by the user.

Pre-processing — In order to reduce noise in skin images such as hair, ink spots, filters are utilized. Transformation of data into a particular format that can be easily processed. The incoming image is transformed into a two-dimensional RGB matrix by the disease detection system. Finally, every image has been shrunk to a uniform size.

Feature extraction — Once the pre-processing is done, feature extraction is carried out. In order to process a dataset, it attempts to decrease the number of features.

Classification — To categorize the images into different classes, classification is done. A trained classifier is used to classify images using a trained dataset.

Result — Final desired result of the model. Recognizing skin disorders and showing users the findings as discovered diseases is the aim of this.

2. SKIN DISEASES WITH SYMPTOMS AND AVAILABLE DATASET

In this section diseases with their symptoms and mostly used dataset for skin disease detection are discussed.

2.1 Diseases with Symptoms-There are various skin diseases and some are discussed below in Table1.

Table1: Skin diseases

S. No.	Disease Name	Description	Image
1	**Acne vulgaris**	It is a frequent type of acne and is described by a blended ejection of fiery and non-incendiary skin injuries. An underlying disease that necessitates medical attention may be the cause of an abrupt onset of severe acne.	
2	**Atopic dermatitis**	It is a chronic skin lesion cause stingling and disturbance, harsh, , with a red rash and dry, toughness.AD is not currently managed in any way. Treatment may include avoiding triggers, making lifestyle changes, and using medication to manage symptoms.	
3	**Benign skin tumors-**	Growth of abnormal area on skin, Ephilis, lentigo simplex, and melanocytic naevus (mole) are typical benign skin lesions of melanocytic origin.	
	Diaper candidiasis	Caused by Fungal infection, Babies that use damp diapers are more likely to experience it, especially if they are unclean. Candidal nappy dermatitis is more likely to occur when you have diarrhoea.	
5	**Carbuncle**	Diabetes mellitus, little pimples on the affected area are all symptoms of infection. The infection can spread to other areas of the person's body or to other persons through skin-to-skin contact or the sharing of personal goods if the boil or carbuncle is active.	
6	**Monkeypox**	It is an infectious diseases caused by monkeypox virus. It causes rash, bumps, and blisters.	

7	**Melanoma**	It can lead to cancer if not detected at early stage. It has melanocytes cells when it grows grow out of control, creates a cancerous tumor. By reducing your exposure to UV radiation, you can lessen your risk of getting melanoma.	
8	**Viral warts**	Exfoliation of the affected area, infection in any place of the organism. Human papilloma virus (HPV) is a form of skin infection that results in warts. Due to their frequent cuts, children are more likely to get warts.	
9	**Measles**	It is a dangerous, highly contagious, and airborne virus-based illness that can have fatal complications and cause skin rashes. It is a virus-based illness spread through the air. The rash at first shows up as level red spots on the face prior to spreading across the body.	

2.2 Dataset- To train and evaluate the deep learning model for identifying skin disorders, the majority of researchers used the following dataset.

2.2.1 HAM 10000[34]

Predictions are done using the HAM10000 dataset. HAM stands for Human against machine and this dataset contains 10000+ images for training purposes for a medical diagnosis model for predicting skin lesion type. This dataset is publicly available on Kaggle, Courtesy of Harvard and Open-source agenda platforms. It has 7 class types which are denoted in Table 2.

Table2: Skin diseases classes

Sl. No.	Classes	Class Name
1	Class I	Melanoma
2	Class II	Melanocytic Nevus
3	Class III	Basal Cell Carcinoma
4	Class IV	Actinic Keratoses
5	Class V	Benign Keratosis
6	Class VI	Dermato Fibroma
7	Class VII	Vascular Lesion

2.2.1 International Skin Imaging Collaboration (ISIC) datasets [35]

This dataset is publically available on these platform- Kaggle. This dataset has different versions 2016, 2017, 2018, 2019, and 2020.2016 dataset contains total of 1279 images. ISIC 2019 has 25,331 images that can be categorised into nine distinct diagnostic groups for dermoscopic images which are commonly used denoted in Table 3.

Table 3: Classes of skin diseases used in ISIC

Sl. No.	Classes (in ISIC)	Class Name
1.	Class I	Benign Keratosis
2.	Class II	Squamous Cell Carcinoma
3.	Class III	Dermato Fibroma
4.	Class IV	Melanocyctic nevus
5.	Class V	Melanoma
6.	Class VI	Actininic Keratosis
7.	Class VII	Vascular Lesion
8.	Class VIII	Basal Cell Cancer

3. BACKGROUND STUDY

In this section, background studies covering the detection methods for predicting diseases are discussed. The detection methods for predicting diseases are evolving over time as new techniques emerge. These methods are becoming more efficient and precise. Some of these are discussed below.

Yuan [1] proposed a model to detect skin lesions — nevus, seborrhoeic keratosis, and malignant melanoma. A CDNN with 29 network layers was used, and ReLU served as the activation function. The model used an online dataset containing 750 images and achieved an accuracy of 78% using Python implementation. Patnaik et al. [2] presented a model to identify dermatological skin abnormalities. Deep learning algorithms such as Inception_v3, MobileNet, ResNet, and Xception were used for feature extraction, while algorithms like Random Forest and Logistic Regression were used for training and testing. The model achieved an accuracy of 88%. To train the system, samples from the entire dataset were used. Mendes [3] proposed a model to predict 12 types of skin lesions using a ResNet-152 architecture trained with over 3,797 images. The model achieved 96% accuracy for melanoma, 91% for BCC, and an overall accuracy of 78%. However, this model had the drawback of relatively low overall accuracy. Anabik Pal et al. [4] proposed a model to predict melanoma disease using a CNN that combines ResNet50, DenseNet121, and MobileNet. The dataset used was ISIC 2018 containing 173 images. The model achieved an accuracy of 77.5%, which was higher than the accuracy of the individual models. Daniel et al. [5] used an online dataset of more than 4,000 images and proposed a CNN-based model using GoogLeNet and Inception v3 for predicting autoimmune blistering diseases. The model achieved an accuracy of 80%. Dilber et al. [6] proposed a CNN model with four convolutional layers and three MaxPooling layers inserted after the 2nd, 3rd, and 4th convolutional layers for classifying monkeypox and chickenpox. It achieved 99% accuracy using a combined dataset from online sources. Gouda et al. [7] developed a CNN-based model (ResNet, Inception) to detect skin lesions using the ISIC dataset and achieved an accuracy of 85%. ESRGAN was used for preprocessing to enhance microscopic-level gradients.

Ghosh et al. [8] developed a model called SkinNet16 for detecting skin cancer. The model, based on CNN architecture, used the Adamax optimizer and PCA for feature selection, achieving 99% accuracy. Balazs [9] proposed an ensemble-based CNN framework trained on 2,750 images and achieved an accuracy of 89%. It classified skin diseases into three classes: benign skin tumor, cancerous melanoma, and seborrhoeic keratosis. Ali et al. [10] presented a deep learning architecture to identify skin cancer using the HAM10000 dataset with Inception v3 and ResNet, achieving an accuracy of 99.77%. Srinivasu et al. [11] developed a model for classifying skin diseases using a DNN with MobileNetV2 and LSTM. Using the HAM10000 dataset, the model achieved 85% accuracy. Its drawback was low accuracy due to the use of fewer significant parameters. Rahman et al. [12] created a CNN-based model to identify acne and rosacea. The model used the sigmoid activation function and binary cross-entropy loss, achieving the highest accuracy of 99% with EfficientNet. Yeong et al. [13] designed a model called WonDerM to detect seven different types of skin lesions. The model achieved 89% accuracy. It involved preprocessing of images, neural network fine-tuning with segmentation data, and an ensemble method for classification. However, low-level features were not considered, which was a drawback. Nils et al. [14] proposed a CNN model using EfficientNets for classifying different skin diseases. It supported multiple image resolutions and used various cropping strategies, achieving 75% accuracy, which was relatively low. Ameri [15] developed a CNN-based model using AlexNet for detecting skin cancer. The model achieved an accuracy of 84%, which was low.

Dusa et al. [16] presented a model to identify melanoma using dermoscopic images, which capture high-resolution details. The ISIC 2019 dataset was used, and CNN architectures such as EfficientNets, SENet154, and ResNet were trained. U-Net was used for segmentation, achieving 88% accuracy. Saket et al. [17] proposed a DCNN-based model to detect skin cancer. Preprocessing was done using Keras Image Data Generator, and ReLU was used as the activation function, achieving 92% accuracy. Rehan et al. [18] developed a CNN-based model to predict melanoma using the Adam optimizer and binary cross-entropy loss function, achieving 97% accuracy. Chiranjibi et al. [19] proposed a deep learning model using an ensemble approach to detect monkeypox, achieving 87% accuracy. The dataset contained 161 images: 43 monkeypox, 47 chickenpox, 17 measles, and 54 normal. The model's drawback was the small dataset and reliance on pre-trained models, which may be unsuitable for memory-constrained deployments. Zhangli [20] proposed a model called FixCaps for skin cancer diagnosis. A CBAM (Convolutional Block Attention Module) was introduced between the convolution and capsule layers to reduce spatial information loss. The model achieved 97% accuracy. Pravin et al. [21] proposed a deep learning method using MobileNetV2 for skin disease prediction and LSTM for performance improvement, achieving 86% accuracy. Hritam et al. [22] proposed a CNN-based model for identifying skin lesions, incorporating Boundary Attention, Reverse

Attention, and Parallel Partial Decoder modules. It used Res2Net and combined two loss functions: Binary Cross-Entropy (BCE) and Weighted IoU, improving segmentation accuracy. Ramzi [23] proposed a DCNN-based model to identify six skin lesions acne, athlete's foot, chickenpox, eczema, skin cancer, and vitiligo achieving 82% accuracy. Low accuracy was its main drawback. Hafidz et al. [24] suggested a CNN model using VGG-16 for classifying monkeypox and measles. The dataset from Kaggle consisted of 360 images (normal, monkeypox, and measles). Preprocessing was done using TensorFlow. Although VGG-16 required long processing time, it provided good performance, achieving 83.33% accuracy.

Wei et al. [25] proposed a CNN-based model to classify skin diseases using DenseNet201 and ConvNeXt_L. It achieved accuracies of 92.12% and 92.88%, respectively. Two datasets were used: HAM10000 and a private hospital dataset containing 2,600 images. The model used the stochastic gradient descent (SGD) and MultiStepLR algorithms for optimization and learning rate adjustment. Vinay et al. [26] presented a CNN model to classify different skin diseases using a dataset of 2,000 images. The images were normalized and converted to grayscale. ReLU was used as the activation function, and the model achieved 98% accuracy. Ameera et al. [27] presented a model to identify monkeypox using five pre-trained deep learning models. MobileNetV2 achieved the highest accuracy of 99%. The dataset consisted of 117 images, which was a limitation. A Deep Convolutional Generative Adversarial Network (DCGAN) was used for augmentation. Rabbia et al. [28] proposed a CNN-based model to detect skin lesions. A GF filter was used for noise removal, Local Binary Patterns and Inception V3 were used for feature extraction, and Adam optimizer was applied for learning rate adjustment. Using LSTM, skin cancer was classified into malignant and benign types, achieving 99% accuracy. Yang et al. [38] suggested a model using ResNet-50, achieving 91% accuracy. The dataset contained 26 classes of skin images along with patient textual data. The study demonstrated the potential of cross-modal AI for skin disease detection. Behara et al. [39] introduced a hybrid method combining the Active Contour Snake model for segmentation and a lightweight attention-guided Capsule Network for classification. The approach achieved approximately 98% accuracy on the HAM10000 and ISIC datasets using ResNet50 features with capsule networks, enabling efficient lesion characterization. Malik et al. [40] proposed a seven-layer CNN model combined with Random Forest for skin image classification. The study reported 87.64% accuracy using ISIC and HAM10000 datasets and emphasized the importance of data augmentation and balanced sampling for improving classification performance between benign and malignant lesions.

3. OVERVIEW OF SKIN DISEASE DETECTION TECHNIQUES

The comparison of different deep learning methods for detection of skin diseases with their accuracies are discussed in Table4. Mostly papers used standard dataset which are available online platforms like Kaggle.

Table 4: Comparison table

Year	Ref.	Dataset Resources	Deep Learning Techniques	Disease	Accuracy
2017	[1]	ISBI	CDNN	Melanoma Detection	78%
2018	[2]	Own dataset	Inceptionv3,MobileNet, Resnet, Xception	Automated Skin Disease	88%
2018	[3]	MED-NODE, Edinburgh	CNN, ResNet-152,	Skin Lesions Classification	78%
2018	[4]	ISIC 2018	ResNet50,DenseNet121 and MobileNet	Melanoma	73%
2018	[9]	private dataset	Essemble CNN	Skin Diseases	89%
2019	[13]	HAM 10000	CNN with (DenseNet and U-net)	Classification of skin lesion	89%
2019	[14]	HAM 10000	CNN,EfficientNet	Skin Lesion Classification	74.2%
2020	[15]	HAM 10000	DCNN, Alexnet	Skin cancer detection	84%
2020	[16]	ISIC 2019	CNN, U net	Classification of skin lesion	88%
2020	[10]	HAM 10000	inceptionv3 and resnet	Skin cancer	99%

2020	[17]	HAM 10000	CNN with ResNeXt101	Cancer classification	92.83%
2021	[5]	Consolidated dataset from online repositories	CNN, GoogleNet Inception v3	Autoimmune Blistering Diseases	80%
2021	[18]	HAM 10000	CNN	Melanoma	97%
2021	[11]	HAM 10000	MobileNetV2 & LSTM	Skin lesion	85%
2022	[8]	PH2and the ISIC datasets	Enhanced CNN	Skin Diseases	99%
2022	[12]	Acne grading classification dataset	Deep CNN’s EfficientNet	Acne &Rosacea Detection	99%
2022	[7]	ISIC 2018	CNN,models (Resnet, Inception)	Skin lesion	85%
2022	[19]	private dataset	Ensemble model	Mpox disease	87%.
2022	[21]	private dataset	MobileNetV2, LSTM	Skin diseases	86%.
2022	[23]	Google images, DermaNet and ISIC18	CNN	Six skin diseases	82%
2022	[20]	HAM 10000	Capsule network, CBAM with pytorch	Skin cancer	96%
2022	[22]	HAM 10000	CNN with Res2Net	Skin lesion	90%
2022	[28]	DermIS dataset	DL-Based Features Fusion and LST	Skin Lesion	99%
2023	[25]	HAM 10000 and private dataset	CNN models (DenseNet201 and ConvNeXt_L)	Skin Lesion Classification	93%
2023	[24]	Kaggle platform	VGG 16	Monkeypox and Measles Detection	84%
2023	[26]	private dataset	CNN with ReLu	Skin Diseases	98%
2023	[27]	private dataset	DCGAN, EfficientNet	Monkeypox disease	99%.
2023	[6]	private dataset	CNN	Monkeypox and chicken pox	99%
2024	[37]	PH2	ANN, SVM	skin diseases	94%
2024	[38]	Private dataset	Resnet50 & LLM	26 skin disease types	91%
2024	[39]	HAM10000 and ISIC2020	Active-contour (snake) segmentation + ResNet50	Skin cancer	98%
2024	[40]	HAM10000 and ISIC	CNN	skin diseases	87%
2025	[41]	HAM10000	Densenet121	skin diseases	98%

4. CONCLUSION AND FUTURE SCOPE

Various researchers are conducting research to predict different skin diseases using deep learning models. Skin-related diseases can be caused by numerous reasons, like lifestyle, age and sex. The classification of skin diseases can be done using different methods, but deep learning techniques are being used for getting more accurate and fast diagnoses of disease. In this study, various deep learning techniques were discussed for detecting different skin-related diseases. The assessment of performance and analysis of deep learning methods in the area of skin disease detections are also discussed. This paper provides a survey on some of the prevalent skin diseases, focusing on their symptoms and predictions using deep learning techniques for early disease detection and timely medical intervention. Future research on skin disease detection can involve multimodal data like genomics, dermoscopy, and history, to increase diagnostic performance. Explainable AI and real-time mobile apps can also increase accessibility, trust, and wide-scale use in clinical practice.

CONFLICT OF INTEREST

The authors declare no conflicts of interest regarding the current research.

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