Skin Disease Classification from Image – A Survey

Conference Paper · March 2020

DOI: 10.1109/ICACCS48705.2020.9074232

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Skin Disease Classification from Image - A Survey

Tanvi Goswami
Dept. of Information Technology
Dharmsinh Desai University,cceptable
Nadiad, India
goswami.tanvi@gmail.com

Vipul K. Dabhi
Dept. of Information Technology
Dharmsinh Desai University,cceptable
Nadiad, India
vipuldabhi.it@ddu.ac.in

Harshadkumar B. Prajapati
Dept. of Information Technology
Dharmsinh Desai University,cceptable
Nadiad, India
prajapatihb.it@ddu.ac.in

***Abstract*— Skin diseases are one of the most common types of health illnesses faced by the people for ages. The identification of skin disease mostly relies on the expertise of the doctors and skin biopsy results, which is a time-consuming process. An automated computer-based system for skin disease identification and classification through images is needed to improve the diagnostic accuracy as well as to handle the scarcity of human experts. Classification of skin disease from an image is a crucial task and highly depends on the features of the diseases considered in order to classify it correctly. Many skin diseases have highly similar visual characteristics, which add more challenges to the selection of useful features from the image. The accurate analysis of such diseases from the image would improve the diagnosis, accelerates the diagnostic time and leads to better and cost-effective treatment for patients. This paper presents the survey of different methods and techniques for skin disease classification namely; traditional or handcrafted feature-based as well as deep learning-based techniques.**

Keywords— Skin diseases, lesions, classification, deep learning, CNN, SVM

I. INTRODUCTION

The largest organ of human body is "Skin", an adult carry around 3.6 kg and 2 square meters of it. Skin acts as a waterproof, insulating shield, guarding the body against extremes of temperature, damaging UV lights, and harmful chemicals. With the rate of 10-12%, the population affected across India from skin disease is estimated at nearly 15.1 Crore in 2013 and which increases to 18.8 crores by 2015[38]. According to statistics provided by the World Health Organization [39] around 13 million melanoma skin cancer occurs globally each year, which shows skin diseases are growing very rapidly. There are many factors responsible for a disease to occur such as UV lights, pollution, poor immunity, and an unhealthy lifestyle. There are two major categories in which the lesions (spot) of skin disease are classified; benign and malignant skin lesions. Most of the skin lesions are benign in nature which is gentle and non-dangerous, whereas those which are dangerous for patient's health and evil in nature are malignant skin lesions such as melanoma skin cancer.

Diagnosis of skin disease from an image is a challenging problem as there exist many skin diseases. Researchers reported following problems during skin disease classification: 1) A disease may have many lesion types. 2) Many diseases may have a similar visual characteristic, which is often confusing for the dermatologist as well to identify the disease by visual inspection. 3) The varying skin colors and skin type (age) introduce more difficulty in computer-based diagnosis. Therefore, relevant feature selection for such diseases is very important in computer-based diagnosis in order to identify it correctly. The success of an automatic system rely on how accurately the system performs and does needed image processing as well as machine learning tasks.

There are many technologies available in the medical science for diagnosis of skin diseases. But, the computer based automatic diagnosis is quite more useful for medical decision support and makes the entire process fast. For example if such automated system is implemented in the healthcare centres then patient does not have to suffer unnecessarily due to unavailability of experts. Further, it is non-invasive method of diagnosis therefore it is not painful. As per 2015 statistics of India [38], for approximately 121 crore of population there are about 6,000 dermatologists providing services in India. This means that for every 100,000 people, only 0.49 dermatologists are available in India as compared to 3.2 in many states of the US [38].

Due to recent advances in the technology large amount of medical data is produced daily and these data contains valuable and crucial information about the patients. The image based artificial intelligence is becoming more popular for certain diseases specially skin diseases. The diagnostic accuracy for computer based system highly relies on the selection of relevant feature, classifier used and the availability of dataset as well as number of images on which the model has been trained. Now a day's for pattern recognition and classification tasks the Convolution Neural Networks (CNN) are highly used. For better understanding of various works done by the researchers, we carry out a survey on different approaches used for the classification of the skin diseases.

This paper is divided into four sections. Section II presents the background knowledge; type of images, and usage of traditional and deep learning based approaches for skin disease classification. Section III presents a survey on traditional or feature extraction based methods as well as CNN based approaches for skin disease identification and classification. Section IV presents the analysis and findings of traditional and CNN based methods and finally, Section V presents the conclusion.

978-1-7281-5197-7/20/$31.00 ©2020 IEEE

II. BACKGROUND KNOWLEDGE

This section is divided into three parts: Skin disease Image type, general process for skin disease classification using traditional techniques and using deep learning based techniques.

A. Clinical and Dermoscopic Images

A clinical image is said to be the image of the patient's affected body part - such as an injury, skin lesion or it can be diagnostic image. The image is captured with normal or digital camera. This type of image may have different lightening, resolution and different angle depend on the type of camera used for capturing the image.

For computer aided diagnosis, dermoscopic images are more useful. These images are produced using dermoscope [16], which is an instrument used by dermatologist to analyze the skin lesions. The dermoscope usually has uniform illumination and more contrast. As the device has bright illumination, the lesions are clear enough for visualization and recognition. Furthermore, processing of dermoscopic images become easy because the images have less noise. Fig.1 (a) illustrates the way to capture dermoscopic image, (b) presents the dermoscopic image and (c) shows the clinical image.

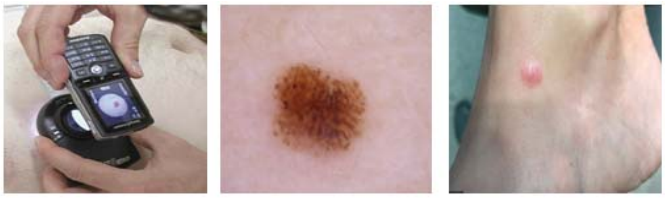

Fig. 1. (a) Image acquisition using Dermoscope (Image source: https://www.researchgate.net/figure/Clinical-A-and-dermoscopic-images-B-of-a-melanoma-case-9_fig2_6302365) (b) Dermocopic Image (c) Clinical Image

B. Skin Disease Classification using Traditional Approach

In the traditional approach, the handcrafted features are fed into the conventional classifier. Fig. 2 shows the general process of skin disease classification using the traditional approach.

1) Input Image

Skin disease image databases for many diseases are available freely. However, some are fully or partially open source and others are commercially available. The input image can be of type dermoscopic or clinical based on the dataset used. Table I contains the information about the availability and details of various datasets. The widely used datasets are [27], [31], [32] and [33].

2) Image preprocessing

Image preprocessing is an important step and it is required because an image may contain many noises such as dermoscopic gel, air bubbles, and hairs.

TABLE I. AVAILABLE DATASETS FOR SKIN DISEASE IMAGES

Dataset	Image	No. Images	Classes	Open source
Derm Net NZ image library[32]	Clinical	20000+	-	Partially
Dermofit Image library[33]	Dermoscopic	1300	10	Yes
ISBI-2016 [27]	Dermoscopic	1279	2	Yes
ISBI – 2017 [27]	Dermoscopic	2750	2	Yes
Ham10000[27]	Dermoscopic	10015	7	Yes
Stanford Hospital [4]	Clinical	-	-	No
Pecking Union medical college clinical database[5]	Dermoscopic	28000	-	No
IRMA Dataset[28]	Dermoscopic	747	2	Not Availabl e
PH2[29]	Dermoscopic	200	2	Yes
MED-NODE[30]	Clinical	170	2	Yes
DermQuest[31]	Clinical	22500	-	Yes
Hospital Pedro Hispano, Matosinhos[14]	Dermoscopic	200	3	No
SD-198 [34]	Clinical and Dermoscopic	6584	198	Yes

However, clinical images require more preprocessing as compared to dermoscopic because of parameters such as resolution, lightening condition, illumination, angle of image captured, size of skin area covered may vary and depends on the person who is capturing the image. These captured images could create problems in the subsequent stages.

The skin hairs can be removed using different filters such as; median [16], average or Gaussian filter [2], morphological operations such as erosion and dilation, binary thresholding [14] and software such as Dull Razor [15], [16]. For low contrast images; lesion or contrast enhancement algorithms [8] are useful. The contrast enhancement with histogram equalization provides better visualization by uniform distribution of pixel intensity across the image and it is one of the most used techniques in literature [16]. For salt and pepper kind of noise; a median or mean filter can give better noise removal results.

3) Image Segmentation

Image segmentation extracts the disease affected area from the normal skin and can play very important role in skin disease detection [16]. Image segmentation can be carried out by three ways: 1) pixel-based, 2) edge-based, and 3) region-based segmentation. In pixel-based segmentation, each pixel of an image is identified to be the part of a homogeneous region or to an object. This can be done using binary thresholding or variant of it [2], [3], [14] and [19]. The edge-based method detects and links edge pixels to form the bounding shape of the skin lesions. For example, Robert, Prewitt, Sobel and Canny operators, adaptive snake or gradient vector flow [9] can be used. The Region-based methods rely on similar patterns in the intensity values within

the neighborhood pixels and are based on continuity. The examples are region growing, merging and splitting, and Watershed algorithm [9], [11].

4) Feature Extraction

The most prominent features which are used to describe and identify skin diseases visually are its color and texture information. The color information plays an important role to distinguish one disease from another. These color features can be extracted using various techniques such as color histograms, color correlograms, color descriptors, GLCM [11], [19]. The texture information conveys the complex visual patterns of the skin lesions and spatially organized entities such as brightness, color, shape, and size. Image texture is basically a function of variation in pixel intensity. GLCM, local binary pattern, SIFT [3] are some techniques used by researchers to get the texture information from the image. In addition to color and texture, each lesion may have different shapes and sizes based on the type of the disease and its severity.

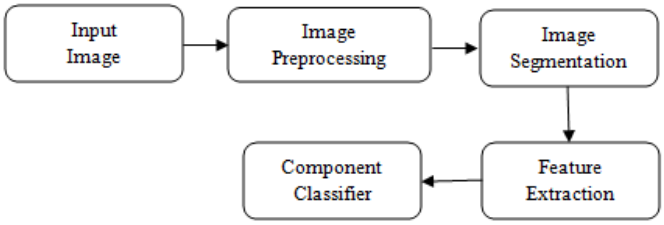

Fig. 2. General/Traditional process of skin disease Classification

5) Classification

Classification is a supervised learning approach for machine learning task. It requires labeled dataset to map the data into specific groups or classes [20]. There are various classification algorithms [16] used to classify the skin disease images such as support vector machine, feed forward neural network, back propagation neural network, k-nearest neighbor, decision trees, etc.

C. Skin Disease Classification using Deep Learning based Approach

Deep Learning is a part of machine learning algorithm inspired by the structure and function of human brain commonly known as neural networks. Convolution Neural Networks (CNN) is a class of deep learning algorithm which is mostly used for analyzing the visual contents such as images and videos. With the development of CNN, there has been dramatic improvement observed to solve many classification based problems in medical image analysis.. The basic process for CNN based skin disease image classification is presented in Fig. 3.

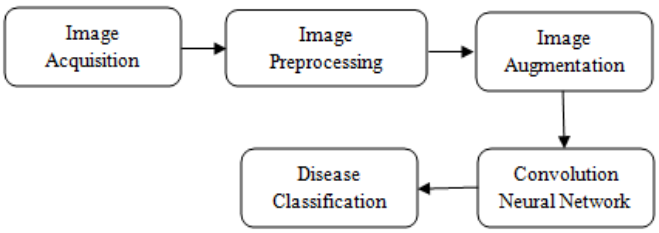

Fig. 3. CNN based approach of skin disease Classification

The process starts with data acquisition. Input to the CNN can be dermoscopic or clinical image, which can be preprocessed if needed; the next step is data augmentation. This results in enough training samples to train the model. Finally the data is fed into the CNN which performs feature extraction and classification by its own. A CNN typically consists of convolution layer in which numbers of filters perform convolution operation on the image and generates feature maps. These feature maps are further down sampled by pooling layers. Finally, the fully connected layer has all the connection from previous layer and does the classification accordingly.

Many researchers have used CNN for skin disease classification via transfer learning or fine-tuning of pre-trained models like Inception v3 [4], [5], [7], ResNet [6], [8], [13], VGG architecture and many more. In transfer learning only weights are optimized if new classification layers have to be added. However, the weights of the original model remain as it is. In fine-tuning the parameters of a trained model must be altered very carefully while trying to validate that model for a dataset with less number of images which does not belong to the train set [40], [41]. Moreover, we need to keep track of the hyper parameters of CNN otherwise the model may have problem of over-fitting. Over-fitting means model learned too well, i.e., it also learns irrelevant information and noise as well which may results in good training accuracy but poor testing accuracy.

III. SURVEY OF LITERATURE

This section presents a survey on both traditional and deep learning based skin disease identification and classification approaches. Table II and III analyzes all major works for both the aforementioned techniques; traditional/handcrafted feature based techniques and deep learning techniques for classification of skin disease from images.

A. Survey onTraditionalTechniques for Skin Disease Image Classification

Amarathunga et al. [2] have come up with expert system limited to classify three diseases. The system consists of two separate units namely; data processing and Image processing unit. The data processing unit was responsible for image acquisition, preprocessing for noise removal, segmentation and feature extraction from the skin disease images whereas data processing unit was employed for data mining task or classification. Five classification algorithms were tested by the

authors namely; AdaBoost, BayesNet, J48, MLP and NaiveBayes. Out of these five the MLP classifier gave better results as compared to other classifiers. However, the data source of images and attributes considered for disease classification is not mentioned.

Chakraborty et al. [3] have proposed a hybrid model using multi objective optimization algorithm NSGA-II and ANN for diagnosis of skin lesion being benign or malignant. The bag-of-features approach is applied to classify the skin lesions and are generated using SIFT. SIFT algorithm identifies and locates the keypoints from the input image and generates the feature vector. Also, to handle large number of keypoints k-means clustering algorithm was used to get representative keypoints where each cluster contains some representative keypoints and these are the generated bag-of-features. These features are then fed to the hybrid classifier where NSGA-II is used to train the ANN. Authors [3] also compared the model's accuracy with ANN-PSO (ANN trained with particle swarm optimization) and ANN-CS (ANN trained with cukoo search.)

The spatial and frequency domain based technique is used by Chatterjee et al. [10] for identification of skin lesion being benign or malignant. The malignant lesions are further classified into subcategories namely; melanocytic or epidermal skin lesions. The cross correlation technique is used to extract regional features which are invariant to light intensity and illumination changes. Also, the cross spectrum based frequency domain analysis has been used for retrieving more detailed features of skin lesions. For classification the SVM classifier was used with three non-linear kernels [10] out of which SVM with RBF kernel gave promising accuracy as compared to other kernels.

TABLE II. SURVEY OF TRADITIONAL TECHNIQUES FOR SKIN DISEASE CLASSIFICATION

References	Disease[a]	Image Type	No. of images	Pre - processing	Segmentation	Feature Extraction[c]	Classifier[b]	Performance Measure
Amarathunga et.al. [2]	Eczema, Impetigo, melanoma	Clinical	-	Y	Thresholding	-	MLP	Accuracy: 90%
Chakraborty et.al [3]	BCC, SA	Dermoscopic	-	-	Thresholding	SIFT	NN-NSGA-II	Accuracy: 90.56% Precision: 88.26% Recall:93.64% F-measure: 90.87%
Manerkar et. al. [11]	Warts, Benign & Malignant Skin cancer	Clinical	45	Y	C-means Clustering and watershed algorithm	GLCM and IQA	SVM	Accuracy: 96-98%
Zaqout et.al. [14]	Benign, Malignant or suspecious lesions	Dermoscopic	200	Y	Thresholding	ABCD rule implementation using entropy,bi-fold,color and diameter	TDS	Accuracy: 90% Sensitivity: 85% Specificity: 92.22%
Chatterjee et. al. [10]	Melanoma,Nevus, BCC,SK	Dermoscopic	6,838	-	-	Cross-correlation,cross spectrum	SVM	Accuracy: 98.79% Sensitivity: 99.01% Specificity: 95.35%
Arifin et.al. [19]	Acne, eczema, psoriasis, Tinea, vitilogo, scabies	Clinical	704	Y	Thresholding	GLCM	feedforward backpropagation ANN	Accuracy: 94.04%
Monisha et. al. [17]	BCC, SA, Lentigo simplex	Dermoscopic	-	Y	GMM	GLCM, DRLBP & GRLTP	NSGA-II-PNN	-

[a]Disease : SK - Seborrheic keratoses, BCC - Basal Cell Carcinoma ,SA-Skin Angioma, [b]Classifier: TDS (Total Dermoscopic score = Asymmetry* 1.3 + Border-Irregularity*0.1 + color *0.5 + diameter*0.5), NSGA-II - Nondominated Sorting Genetic Algorithm, [c]Feature Extraction: GMM- Gradient Mixture Model, GLCM-Grey level co-occurance matrix, IQA-Image Quality Assessment, PNN- probabilistic Neural Network

B. *Survey on deep learning based approach for Skin Disease Image Classification*

Esteva et al. [4] were first to report about how the image classifier convolutional neural netwok (CNN) can achieve the performance similar to the 21 board-certified dermatologists for identification of malignant lesions. The 3-way disease partition algorithm was designed to classify a given skin lesion to be malignant, benign or non-neoplastic. Also, 9-way disease partition was performed to classify a given lesion into one of the 9 mentioned categories. The state-of-the art InceptionV3 CNN architecture was used for skin lesion classification [4] has concluded that the CNN can outperform human experts if it is trained with enough data. Also, [4] has concluded that the CNN can outperform human experts if it is trained with enough data.

Zhang et al. [5] also used InceptionV3 architecture with modified final layer to classify 4 diseases. The model was trained on two nearly similar datasets of dermoscopic images. Authors [5] concluded that misclassification can occur due to presence of multiple disease lesions on the single skin image.

Sun et al. [24] have proposed handcrafted feature based as well as CNN based approaches for classification of clinical images. They trained four CNN architectures namely; Caffenet, fine-tuned Caffenet, VGG and fine-tuned VGGNet. Out of these four the fine-tuned VGGNet gave quite good accuracy. The accuracy of VGGNet was similar to that of the handcrafted feature which was generated by 7 different methods namely; SIFT, HOG, LBP, and color histogram with SVM classifier. However, the architectures and use of benchmark dataset plays an important role for skin disease image classification to achieve good accuracy.

Gessert et al. [37] introduced patch based method to obtain fine-grain differences between various skin lesions from high resolution images. The high resolution images are divided into 5, 9, and 16 crops or patches and these images patches or crops are fed to the standard CNN architectures. Three architectures were used by the authors namely; Inception v3, DenseNet and SE-Resnext50 architecture [37] for prediction of disease from high resolution image patch.

Rehman et al. [22] have proposed CNN architecture by setting 16 different filters of 7*7 kernel size with pooling layers for down sampling. The proposed model was trained for malignant and benign category of diseases namely; melanoma, Seborrheic keratosis and nevus. The RGB channels of the segmented image are normalized with zero mean and unit variance. This normalized matrix was fed to CNN for feature extraction, further the fully connected layer consists of 3 layer ANN classifier which classify the skin lesion being banign or malignant.

Kulhalli et al. [7] has proposed a 5-stage, 3-stage and 2-stage hierarchical approach to classify 7 diseases using InceptionV3 CNN architecture. The authors have addressed the class imbalance problem by using image augmentation technique in order to balance the category classes. The 5-stage classifier gave better result as compared to 2 and 3-stage hierarchical classifiers. Further, the authors [7] suggested that the model can be further fine-tuned and ensemble based methods might help in order to improve the classification performance.

IV. ANALYSIS & FINDINGS

Both traditional, as well as CNN based approaches are useful for the classification of skin diseases.

The traditional methods require appropriate feature extraction as well as segmentation method for skin diseases. Further, it is important to identify the relevant features and discard irrelevant features as the classification often depends on features selected. Therefore, if irrelevant features got selected then it may lead to misclassification. However, contrary to CNN traditional approach does not require a large size dataset.

CNN can learn the features of the skin diseases automatically. It selects the filters intelligently as compared to the traditional or manual way of selecting filters in traditional approach to extract the relevant features from the images. Therefore, no feature extraction method is needed in CNN based approach. However, pretrained models can be used to classify the skin diseases but these models are heavy in terms of: 1) number of parameters, 2) number of layers, 3) selection and fine-tuning of the appropriate pre-trained model and 4) The model has to be trained from scratch as it is not been trained for skin disease images.

However, CNN can also be designed from scratch. The following criteria are important whenever CNN architecture is designed to classify skin diseases:

1) Dataset: The availability of large dataset is very important as CNN learns much efficiently whenever it's been trained with enough data. The large dataset of clinical images are available on [31], [32]. For dermoscopic images the large datasets are published by ISIC [27].

2) Hyperparameters of CNN: The network structure is determined by the hyperparameters. These hyperparameters are supposed to be set before training the CNN. The parameters which define the network structure are number of hidden layers, dropout, kernel size, number of kernels, batch size, number of epochs, activation function, learning rate, etc.

3) Computational Power: The main challenge of training CNN is the availability of computational resources. There are thousands of trainable parameters on CNN; therefore it is computationally costly as compared to the traditional way of classifying skin disease. To train the CNN GPU availability is a must. Also, the training time is more and it depends on the size of the dataset used to train the model.

TABLE III. SURVEY OF DEEP LEARNING BASED SKIN DISEASE CLASSIFICATION

Reference	Disease classes	Image type	No. of images	Dataset	Additional (Preprocessing/ Segmentation)	CNN Architecture	Performance Measures
Sun et al. [24]	Wide Variety	Clinical	6,584	SD-198 [34]		Fine-tuned VGG19	Accuracy: 50.27%
			5,619	SD-128[24]			
Esteva et al. [4]	Malignant and Benign skin lesions	Clinical	129,450	ASIC[27], Edinburgh Dermofit Library[33], Stanford Hospital [4]		Inception V3 with PA (partition algorithm)	Accuracy: 72.1 ±0.9%
		Dermoscopic	3,374				
Zhang et al. [5]	Melanocyticn evus, SK BCC, psoriasis.	Dermoscopic	1,067	Dataset A [5]	-	Inception v3	Dataset A: Accuracy: 87.25 ± 2.24%
			522	Dataset B [5]			Dataset B: Accuracy:86.63% ± 5.78%
Rehman et al. [22]	Malignant and Benign skin lesions	Dermoscopic	379	ASIC-2016 [27]	Segmentation using Generalized Gaussian Distribution	CNN With Conv : 16 filters of 7*7, pooling layer:16 FC: 100*50*5	Accuracy: 98.32%
							Sensitivity: 98.15%
							Specificity: 98.41%
Brinker et al. [6]	Melanoma and Nevi	Clincal	-	HAM10000 [27]		ResNet50	Mean Sensitivity: 89.4%
		Dermoscopic	12,378				Mean Specificity: 64.4%
							ROC: 0.769
Kulhalli et al. [7]	Melanoma, Nevi, SK, Akiec, BCC, DF, BKL	Dermoscopic	10,015	HAM10000 [27]		InceptionV3	Normalized F1 Score : 0.93
Khan et al. [8]	Melanoma Vs other	Dermoscopic	1,279	ISBI-16[27]	Lesion Enhancement	ResNet50 and ResNet101	Accuracy: ISBI 2016 : 90.20%
			2,790	ISBI-17[27]			ISBI 2017 : 95.60%
			10,000	HAM10000 [27]			Ham1000: 89.8%

V. CONCLUSION

This paper is focused on various techniques for classification of skin diseases. Automating the process of skin disease identification and classification can be very helpful and takes less time for diagnosis as well. This paper presents the survey of traditional or feature extraction based and CNN based approach for skin disease classification. From the study it is concluded that for traditional approach the feature selection process is time consuming also selection of relevant feature is very important. Whereas, the deep learning algorithm CNN learns the features automatically and efficiently, for feature extraction CNN selects the filters intelligently as compared with manual ones. The pre-trained models like Inception v3, resnet, VGG16, VGG19, Alexnet etc are trained on very large dataset with millions of general images and can be used with transfer learning or fine tuning. However, the pre-trained model has to be trained from scratch if it is not being trained with skin disease images before. Also, the CNN needs quite big dataset for training so it can learn effectively as compare to the traditional way of skin disease classification.

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