Abstract: Skin diseases are a frequent problem among all age groups. Application of Machine Learning (ML) is exceedingly suitable for skin diseases identification as it has large clinical image database that can be used to train models and interpret diagnosis for better patient outcomes. Researchers have used various image processing techniques and classification methods. Color and Texture based features are most commonly used for image analysis and Convolutional Neural Network (CNN) has become current standard practice in classifying skin disorders. This paper presents a thorough survey of image processing techniques and classifiers for skin diseases detection.

Keywords: Image Processing, Machine Learning, Neural Networks

I. INTRODUCTION

Skin is the largest sensory organ of our body. Dermatology is the field of medicine concerned with the diagnosis, treatment and prevention of skin disorders. Dermatology deals with morphological features and in majority of cases, diagnosis are based on visual image recognition. Application of Machine Learning (ML) is particularly important due to its’s ability for image recognition and classification [1]. A study published in Nature [2] demonstrated that deep learning can classify skin cancer with a level of expertise comparable to dermatologists.

Skin disease detection system based on ML is becoming an important tool for clinical diagnosis of skin diseases. Such system will assist in diagnosis, particularly in enhancing accuracy and sensitivity of identification of skin lesions and rashes, thereby improving patient care [3]. In India, large number of population consults General Practitioners for skin diseases [4]. Such systems could help them to narrow down their differential diagnosis [5]. A typical skin disease recognition system includes series of steps like acquiring the image, pre-processing it, extracting significant features and finally classifying the diseases. This paper presents a comprehensive survey on dermatological disease classification systems utilizing image processing and neural networks.

II. ARCHITECTURE OF SKIN DISEASE DETECTION SYSTEM

Skin disease recognition system involves four main steps (1) Image sensing and Acquisition (2) Pre-Processing of skin image (3) Skin Feature Extraction (4) Disease classification by suitable classifiers.

(1) Image sensing and Acquisition: Dermoscopic images as well as macroscopic images (clinical images) are extensively used in the ML based techniques for diagnosis of skin diseases. Macroscopic images are captured from smart phone cameras or digital cameras whereas dermoscopic images are acquired from dermatoscope and have the advantage of enhanced visualization of different pigment patterns on skin surface.

(2) Image Pre-Processing: The images acquired from different sources like digital camera or by dermoscopy vary in size and resolution and hence pre-processing is the first step required for producing good quality image. Image pre-processing steps involves standardizing the image by resizing and by removal of unwanted noise like hair, air bubbles and skin pigments with the help of filter. Then by the process of data augmentation like flipping, rotation etc. and segmentation, the image is represented into more meaningful form for easier analysis [8]. Segmentation helps in extracting the region of interest i.e. affected area from background image.

(3) Skin Feature Extraction: This step reduces the dimension of image by removing the redundant information without losing the relevant data. Feature extraction algorithms are used to detect features such as shape, edges or texture in a skin image. There are three commonly used feature extraction algorithms for detection of skin lesions.

- Geometrical Features: These are the features obtained from set of geometric elements like points, lines or curves. Image geometrical features include Asymmetry, Border, Colour and Diameter (ABCD) features.

- Color Features: Color feature extraction is used after the segmentation to identify visible color of image. The various statistical color feature descriptors are mean, variance, standard deviation and skewness.

- Texture Features: Texture is the property of surface which gives important information about the structure of surface.
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- It is a function of spatial variation in pixel intensity in an image [6]. The two widely used texture feature algorithms are local binary pattern operator (LBP) and gray level co-occurrence matrix (GLCM). The various GLCM statistical parameters are Energy, Entropy, Variance, Correlation and Homogeneity.
- All these features together form a feature vector and is used for training the classifier.

(4) **Classification**: Classifier models are trained on input feature extracted from processed image and then trained models are used for testing new images. This categorizes the images into one of the pre-defined diseases class. The commonly used classification algorithms are Linear Discriminative Analysis (LDA), Naïve Bayes Classifier (NB), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) [7]. Fig. 1 shows the process of skin disease detection.

Authors of [11] have proposed automatic detection of two misdiagnosed diseases (eczema and psoriasis) by combining both visual and non-visual aspects of diseases. Through K-means clustering segmentation algorithm and by combining categorical and texture features, system achieves accuracy of 84%.

Authors of [12] compared dermatologists and CNN for onychomycosis detection. CNN model trained with clinical images achieved greater accuracy in diagnosing onychomycosis compared to dermatologists. The classifier achieved specificity range of 69.3-96.7%, sensitivity range of 82.7-96.7%.

Authors of [13] used three deep learning algorithms for automatic skin disease detection. Inception V3, Inception ResNet V2 and MobileNet are used for extracting features. Logistic Regression & Random Forest classifiers aided in training and testing the model. This system shows 88% efficiency in classifying 20 diseases accurately. Combining all 3 models has the potential of further improving accuracy.

P R. Hegde et al. [14] extracted GLCM and color features of three diseases and applied LDA, SVM and ANN classifiers. The results proved that LDA and color features is better in two as well as multiclass classification whereas SVM shows better accuracy for multiclass using texture feature and for binary class using hybrid features.

Li-sheng Wei et al. [15] applied water shed algorithm for image segmentation and after extracting GLCM and color features, results are tested with SVM classifier. The proposed method showed improvement in accuracy as compared to other techniques by combining texture and color features.

The authors of [16] worked on the segmentation and automatic classification of Psoriasis skin biopsy images. Super pixel technique is used for segmentation and classification is done by deep CNN model. Results showed CNN with feature based classifiers gives accuracy of 95.17% and are more efficient than hand-crafted feature based classifiers like SVM, RF and KNN.

In [17] author used pretrained deep CNN for feature extraction and classification of four common cutaneous diseases and tested their performance with the help of experienced dermatologists. Results showed that the average accuracy of evenly distributed dataset is slightly less than uneven dataset. Author also describes four major reasons of misclassification of a disease.

### III. LITERATURE SURVEY ON IMPLEMENTATION OF IMAGE PROCESSING AND NEURAL NETWORK SYSTEMS FOR SKIN DISEASE DETECTION

Table-I shows summary of work on dermatological skin disease detection using image processing and neural networks.

Rahat Yasir et.al [8] trained neural network with user input features like liquid, age, gender, feeling, elevation etc. and image extracted features like color, shape, area etc. and tested it for 775 skin images of 9 diseases. The proposed model performs better with high elevation features and has low detection rate for low elevation features in affected area.

In [9], authors developed border detection algorithm for identification of non-melanocytic skin lesions (NoMSLs) and melanocytic skin lesions (MSLs). Layer model and flat model are proposed for the classification task and results indicate that layered model perform better than flat model.

Shrivastava VK et al [10] have developed a psoriasis risk assessment system (PRAS) that helps dermatologists in analyzing psoriasis disease at an early stage. Experiments are conducted using several combinations of feature selection methods and classifiers and optimal results are obtained.
<table>
<thead>
<tr>
<th>Author &amp; Year</th>
<th>Disease Type</th>
<th>Feature extraction method</th>
<th>Classifier</th>
<th>No of images (Type)</th>
<th>Evaluation measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rahat Yasir, A Rahman, and Nova Ahmad 2014 [8]</td>
<td>Acne, Acne, Pore, Leprosy..</td>
<td>Geometrical, color, user input features (Gender, Age, feeling etc)</td>
<td>ANN</td>
<td>775 (C)</td>
<td>ACC(Porior, Foot Ulcer, Vitiligo): 90%, ACC(T Corporis, P Rosea): 85%</td>
</tr>
<tr>
<td>Ulvi Withana, Pumudu Fernando 2017 [11]</td>
<td>Eczema, Psoriasis</td>
<td>Texture, Area-To-Perimeter Ratio, Categorical variables</td>
<td>SVM</td>
<td>100 (C)</td>
<td>ACC: 100%</td>
</tr>
<tr>
<td>Han SS et al. 2018 [12]</td>
<td>Onychomycosis</td>
<td>CNN (convolutional layer)</td>
<td>CNN</td>
<td>49,567 (C)</td>
<td>SP: 69.3-96.7%, SE: 82.7-96.7%.</td>
</tr>
<tr>
<td>Li-sheng Wei, Quan Gan and Tao Ji 2019 [15]</td>
<td>Herpes, Dermatitis, Psoriasis</td>
<td>GLCM Texture, Color Feature, Vertical Image Segmentation</td>
<td>SVM</td>
<td>90 (C)</td>
<td>ACC: 90%</td>
</tr>
<tr>
<td>Anabik Pal et al. 2018 [16]</td>
<td>Psoriasis</td>
<td>Superpixel segmentation-SLC</td>
<td>U shaped fully convolutional neural network(FCN)</td>
<td>90 (C)</td>
<td>ACC: 95.17%</td>
</tr>
<tr>
<td>Xinyuan Zhang et al. 2018 [17]</td>
<td>Melanocytic nevus, SK, BCC, Poreiosis</td>
<td>Pooling, convolutional layers of Inception v3 model</td>
<td>DCNN</td>
<td>Dataset A: 1067, Dataset B: 528(D)</td>
<td>ACC(Dataset A): 87.25%, ACC(Dataset B): 86.6%</td>
</tr>
<tr>
<td>Mohammed A. Al-masni et al. 2018 [18]</td>
<td>Melanoma, SK</td>
<td>CNN (convolutional layer)</td>
<td>FrCN</td>
<td>2750 (D)</td>
<td>Jaccard index - 77.11%, ACC (Melanoma): 90.78%, ACC(SK): 91.29%</td>
</tr>
<tr>
<td>Jordan Yap, William Yolland and Philipp Tschand 2018 [20]</td>
<td>Naevus, Melanoma, BCC, SCC, Pigmented Benign Keratosis</td>
<td>CNN (Pooling layers)</td>
<td>2 ResNet-50</td>
<td>2917 (C,D)</td>
<td>AUC:86.6%</td>
</tr>
<tr>
<td>R. B. Oliveira et al. 2019 [21]</td>
<td>Melanoma</td>
<td>Hybrid-Shape+Color+Texture features Feature Selection: GRFS, CFS</td>
<td>KNN, Bayes net, MLP, OPF</td>
<td>1104 (C)</td>
<td>ACC (GRFS+MLP): 90.6 % ACC (CFS + OPF): 91.6%</td>
</tr>
<tr>
<td>Nawal Soliman 2019 [22]</td>
<td>Eczema, Melanoma, Psoriasis</td>
<td>Pre-trained CNN</td>
<td>SVM</td>
<td>80 (C)</td>
<td>ACC: 100%</td>
</tr>
<tr>
<td>Muhammad Qasim Khan et al. 2019 [24]</td>
<td>Melanoma, Neus</td>
<td>Hybrid - GLCM+LBP + color features</td>
<td>SVM</td>
<td>397 (D)</td>
<td>ACC (Color feature + SVM): 77%, ACC (Hybrid Feature + SVM): 96%</td>
</tr>
<tr>
<td>Belal Ahmad et al. 2020 [27]</td>
<td>Acne, Spots, Blackheads, Dark circles</td>
<td>Triplet loss functions for discriminative features</td>
<td>Deep CNN models, ResNet 152, Inception ResNet V2</td>
<td>14000 (C)</td>
<td>Better ACC , SP</td>
</tr>
</tbody>
</table>
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CNN convolutional neural network, SK seborrheic keratosis, SCC squamous cell carcinoma, F-FCN full resolution convolutional network, KNN k-nearest neighbor, SVM support vector machine, LDA linear discriminative analysis, ANN artificial neural network, DCNN deep convolutional neural network, BCC basal cell carcinoma, AURCO area under receiver operating characteristics, LR logistic regression, RF random forest, DT Decision tree ACC accuracy, SP specificity, SE sensitivity, OPF optimum path classifier, C clinical, D dermoscopic

In [18] author proposed automatic segmentation method using Full resolution convolutional networks. This technique extracts full resolution features and does not require any other processing. Results exhibit better performance than Fully Convolutional Network (FCN), SegNet and U-Net deep learning algorithms.

Authors of [19] tested performance of three different pre-trained CNN architectures on 10135 dermoscopic images and classified 8 categories of skin diseases. Results proved that all these models are 11% more accurate than highly skilled dermatologists.

In [20] authors have done combined analysis of clinical, dermoscopic images and patient metadata demonstrated that the multi modal classifier outperforms single classifier in distinguishing multiple skin diseases.

Robert B. et al [21] used various combinations of features like texture, shape and color features for feature extraction of skin cancer images. Several feature selection methods like gain ratio-based feature selection (GRBFS), correlation based feature selection (CFS) are used along with different classifiers and their performance are compared for obtaining better results. Results showed Optimum Path Forest (OPF) classifier gives accuracy of 92.3% without feature selection and 91.6% accurate with correlation feature selection Algorithm.

In [22], authors proposed image processing based system for the detection of three common skin diseases (eczema, melanoma, psoriasis). It includes pre-processing by resizing the image and feature extraction using pretrained five layer AlexNet-CNN model. SVM classifier is used for four class classification. The system achieves 100% accuracy in detecting all three diseases.

In the work presented in [23], first texture features are extracted using local binary patterns, gray length run length matrix, and histogram oriented gradient operators. Then these in combination with ABCD features are optimized using two particle swarm optimization algorithms. Finally combination of KNN, SVM and Deep CNN models are used for classifying skin diseases. All experiments are done on medical dataset from UCI - ML repository and Dermoscopic skin lesion images.

In [24] author proposed a system consisting of hybrid feature extraction techniques like combination of color, GLCM and LBP features which results in significant improvement in accuracy. Centroid selection approach for K-means clustering algorithm for segmenting the images is effective as compared to standard method. Statistical results showed that hybrid feature method provides better results than individual feature extraction methods.

Authors of [25] proposed detection of Vitiligo using average results of three pretrained CNN models trained on RGB, HSV and YCrCb color space images. The applied strategy provides classification accuracy of 87.8 % and performs better than individual networks.

In [26] author tested 3 CNN architectures for 3 classes of acne severity: clear, mild and severe. Inception V4 achieves highest accuracy of 67% on larger image size proving deep learning is efficient for large data set and high resolution images. Approached discussed in [27] uses Triplet loss function along with deep CNN ResNet152 and Inception ResNet-V2 models for achieving better accuracy in effective classification of skin diseases. In Triplet loss function method L2 distance is calculated among images in Euclidean space and on the basis of distance, images are classified into 4 categories as acne, dark circles, blackheads and spots.

IV. CONCLUSION

This survey focuses on image processing techniques and neural networks employed for the detection of various dermatological disorders.

Recent trends and issues related to detection of various dermatological disorders using image processing and neural networks can be summarized as:

Majority of the research work has been done on detection of skin cancer compared to that of other common skin diseases such as psoriasis, eczema, acne, vitiligo etc. Within skin cancer, majority of research has been done on Melanocytic Skin Lesion whereas non-melanocytic skin lesions are relatively neglected.

Dermoscopic and clinical images have been extensively used for diagnosis however dermoscopic images provide better visualization and fine details.

Combinations of color and texture features are considered more frequently for feature extraction in majority of studies.

Various classification methods including SVM, LDA, KNN etc. have been utilized for skin disease classification, however, End to End trained CNNs have become current standard practice. Ensemble methods combining different classifiers have shown improved predictive performance of detection system.

In diagnosis of skin diseases, dermatologists usually identify based on other information (patient history, age, demographics etc.) than only images. This information should be embedded in algorithm to get better accuracy in diagnosis.

REFERENCES


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