Machine Learning Algorithms based Skin Disease Detection

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Abstract—Skin disease recognition and observing is a major challenge looked by the medical industry. Because of expanding contamination and utilization of lousy nourishment, the tally of patients experiencing skin related issues is expanding at a quicker rate. Well-being isn't the main concern, however unfortunate skin hurts our certainty. Customary and appropriate skin checking is a significant advance towards early discovery of any destructive or starting changes in skin that may bring about skin disease. Machine learning methods can add to the improvement of capable frameworks which can order various classes of skin illnesses. To identify skin maladies, first, it is required to separate the skin and non-skin. In this paper, five diverse machine learning algorithms have been chosen and executed on skin infection data set to anticipate the exact class of skin disease. Out of a few machine learning algorithms, we have worked on Random forest, naive bayes, logistic regression, kernel SVM and CNN. A similar examination dependent on confusion matrix parameters and training accuracy has been performed and delineated utilizing graphs. It is discovered that CNN is giving best training precision for the right expectation of skin diseases among all selected.

Keywords: Machine learning, Random forest, naive Bayes, logistic regression, kernel SVM and CNN

I. INTRODUCTION

Skin is the biggest organ of the human body. It is made out of epidermis, dermis, and subcutaneous tissues. Skin perceives the outside condition and shields our inside organs and tissues from unsafe microscopic organisms, contamination and sun presentation. Skin can be influenced by various external and internal factors. Artificial skin harm, chemical harm, adventitious viruses, individual's immune system, and genetic disorders are some factors that influence skin disorders. Skin diseases seriously affect once life and well-being. Ones in a while, individuals attempt to fix their skin issues by utilizing their home cures. These strategies if are not proper for that kind of skin illness would bring about hurtful impacts. Skin diseases can easily transfer from one person to another, thus required to be controlled in an early stage. In maximum cases, the conclusions on the patient's symptoms are tracked from doctor's experiences and subjective judgments. If the judgment is wrong or delayed, it may harm human health. Therefore, it becomes necessary and significant to develop efficient approaches to detect and diagnose the symptoms of skin diseases at early stages. With the advancement of technology, the skin observing framework can be structured and executed for early detection of skin infections. Various innovations are accessible for image and pattern-based discovery of different skin diseases. Machine learning is one of the areas which can play a massive role in operative and exact identification of different classes of skin diseases. Through image classification using machine learning, diseases may be classified. Image classification is a supervised learning issue in which a lot of objective classes is characterized and a model is trained to perceive the class. There exist many machine learning and deep learning algorithms which can distinguish and predict different categories of skin diseases based upon their classifications. This paper presents a comparative analysis of 5 different machine learning algorithms random forest, naive Bayes, logistic regression, kernel SVM and CNN. All these algorithms are implemented on three different types of skin diseases (acne, lichen planus and sjs ten) and perform classification based detection. Almost 3000 skin samples have been compiled for developing and validating the proposed framework. The training accuracy of these algorithms is compared and analyzed. The organization of our work is as follows. Section II explains a brief literature survey of skin problem and melanoma detection. Section III denotes overview of skin diseases and machine learning algorithms. Section IV describes the result from the investigation. Finally, section V gives a conclusion and future scope.

II. LITERATURE SURVEY

The amalgamation of technology with health care results in rapid development in image processing techniques to aid the medical field. Application of digital image-based equipment such as Computed Tomography (CT), Digital Subtraction Angiography (DSA), and Magnetic Resonance Imaging (MRI) help in accurate diagnosis. Many researchers have worked for detection of skin diseases so far. A brief literature survey is given below. Ercal et al. [1] used an adaptive color metric from the RGB planes. It helps in discriminating the tumor and the background. Image segmentation is performed using a suitable coordinate transformation. Borders are drawn by extracting the tumor portion from the segmented image. This was an effective method to find tumors diagnosis. Demyanov et al.

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[2] used deep convolutional neural networks, image classification algorithms with data augmentation to successfully investigate automatic detection of dermoscopic patterns and skin lesion analysis. Ganster et al. [3] developed a computer-based system for image analysis acquired through ELM. Basic segmentation algorithms with fusion strategy are used to get the binary mask of skin lesion. The malignancy of lesion is calculated based upon shape and radiometric features. The local and global parameters are also considered for better results. The system improves the early detection of malignant melanoma. Grana [4] provided a novel mathematical approach to assess the lesion boundary. The approach considers luminance values along a direction normal to the contour at each point. Sigurdsson et al. [5] classified skin lesion based on in vitro Raman spectroscopy. They used a nonlinear neural network classifier for their work. Unique bands in spectrum show explicit lipids and proteins which provides information to diagnose skin lesions. Aberg et al. [6] uses electrical bio-impedance to assess skin cancers and lesions. Multi-frequency impedance spectra are used to separate skin cancer and benign nevi. Wong et al. [7] proposed a novel iterative stochastic region-merging approach to segment skin lesion regions from the macroscopic images. In this approach initially, stochastic region merging is performed on a pixel level, and afterwards on a region level until convergence. Wighton et al. [8] performed automated skin lesion diagnosis. A model based on supervised learning and MAP estimation are presented for the diagnosis. Emre Celebi et al. [9] uses ensembles of thresholding methods to detect lesion borders in dermoscopy images. Oyola and Arroyo [10] collected and classify an image of varicella through Hough transform and applied the color transformation, equalization and edge detection techniques of image processing. It helps in better diagnosis of varicella detection. Hung and Sapiro [11] suggested a method for skin lesion detection built on a partial differential equation. Based upon the morphological filtering through PDE, a contour model of lesions was taken out. It helps in accurately identifying the disease. Three-dimensional computed tomography (CT) imageological technique was applied by Zhong et al. [12]. The technique diagnosed psoriasis vulgaris with high sensitivity and specificity. An innovative approach for auto segmentation and classification of skin lesion was given by Sumithra et al. [13]. The proposed approach uses SVM and k-Nearest neighbor algorithm for lesion detection. Lu et al. [14] employ two-dimensional digital image segmentation and resizing to classify smooth pixels combining the above techniques with Markov random field (MRF). A reliable segmentation technique is established. Salimi et al. [15] classified different skin diseases using a pattern recognition method. Kolkur et al. [16] present a novel skin detection algorithm which enhances the detection of skin pixels, including RGB, HSV, and YCbCr color models. Kotian and Deepa [17] studied auto diagnosis system for skin disease. Techniques such as image border identification and feature data mining are implemented using matlab software. Kumar and Singh [18] relate skin cancer images across different types of neural network. A collection of skin cancer images was trained and tested using Matlab. It helps in the classification of skin cancer. A lot of research and applications are already running in the field of medical imaging and diagnosis. Still we have to concentrate on giving skin monitoring frameworks which are progressively exact, low cost and reliable.

III. OVERVIEW OF SKIN DISEASE AND MACHINE LEARNING ALGORITHMS

Healthy and sparkling skin is the main sign of a sound body. Our skin is a wall against the infections and pollution in the environment and in this way can without much of a stretch get harmed if not dealt with. Skin diseases are very common and fluctuate incredibly in side effects and seriousness. Sometimes the skin diseases are temporary and sometimes permanent or even life-threatening. The reasons may be external environ- mental factors or internal genetic factors. It is a common skin disease generally occurs due to bacteria, hormones, dead skin cells ingrown hair, etc. Acne is mostly found on the face, neck, shoulders, chest, and upper back.

It can be in the form of black/white heads, pimples, cysts or painful nodules. If these are not cured, may result in bad scars or dark skin. Fig. 1(b) is an image of Lichen planus which is a chronic inflammatory and immune-mediated disease. It affects the skin, nails, hair, and mucous membranes [19] Some of the potential causes of this disease are viral infections, allergens, stress, and genetics. Lichen planus is not a contagious disease. The most common symptoms of this disease are purplish-coloured lesions or bump with flat tops on skin or genitals, itching, a lacy-white painful lesion in the mouth, scabby blisters and thin white lines over the rash. Fig. 1(c) shows image of Stevens Johnson syndrome (SJS) and toxic epidermal necrolysis (TEN) is a type of severe skin reaction. Early symptoms of SJS include fever, sore throat, and fatigue followed by blisters and peels. Complications include dehydration, sepsis, pneumonia, and multiple organ failure. Patients suffering from these disorders commonly experience burning pain in their skin [20]. SJS has mostly risen from an immune system and genetic disorders, drug reactions or infections. [21] [22]. The disease is commonly misdiagnosed and therefore treated with antibiotics.

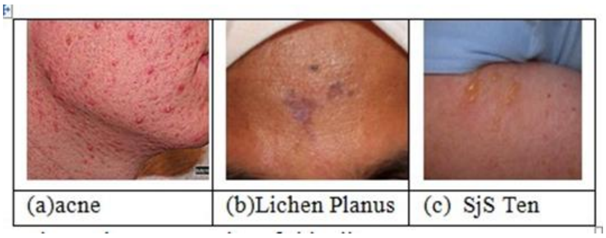

Fig. 1. Sample images of three categories of skin diseases

Machine learning is an implementation of Artificial Intelligence that empowers a structure to learn without being customized accordingly. The innovation is chipping away from the creation of self-learning PC programs that enter, bring in and enhance from their very own knowledge the data given to them. In many areas, machine learning can be implemented, for example, medical diagnosis, image processing, prediction, classification, learning association, regression, and so on. Among these fields, we are implementing image recognition and classification techniques of machine learning.

Image recognition technique teaches a computer to perceive the visual components inside an image and classification technique enables the system to learn the instance and map it to one of numerous classes. For recognition, a big image database is used and learns emerging image characteristics and parameters. We are updating five machine learning algorithms for the classification of skin disease called logistic regression, kernel SVM, Nave prejudice, random forest and CNN. Below is a short explanation of the above algorithms. Logistic regression under supervised learning algorithms is one of the vital binary classifiers. A set of predictors is used by logistic regression to allocate one of the two classes. The target variable can only take discrete values for the specified set of characteristics (or inputs) in a classification problem. In case of multiple logistic regressions, classifiers are trained for all the n classes in a dataset. One classifier for each of the n classes is trained. While training the classifier for class 1, the input data of class 1 labels as positive samples, rest all classes as negative samples. Correspondingly for class 2, the input data of class 2 labels as positive samples and rest all as negative samples. The same process follows for different classes too. Once all the classes are trained, prediction function works and selects the class for which the classifier outputs the highest probability. It returns the class label (1, 2,..., or n) based upon the prediction. The one-vs-all function will pick the label with the highest probability.

Support vector machine categorizes the training data as points in space by a clear and wide gap. Input data is then mapped into the same space and predictions are made to categorize the data into a class based on which side of the gap they fall. This algorithm is very effective in high dimensional spaces. It also saves memory by using a subset of training points in the decision function. The highlighted pixels in Support vectors help in creating the image boundaries. A kernel function is used to define the higher dimensional space.

Nave bayes is a simple and probabilistic classification technique based on Bayes' Theorem. Simply, the classifier works on the assumption that the existence of a particular feature in a class is conditionally distinct with the presence of any other feature. The algorithm initializes the classifier by identifying the prerequisites to train a Nave Bayes classifier. It calculates the prior probability for given class labels. Using Bayes Theorem, the conditional probability with each attribute with each class is calculated. It multiplies the same class conditional probability. Then it multiplies prior probability with a probability calculated in the previous step. Finally, the algorithm checks for the class with the highest probability. Highest probability class belongs to the given input set. The most noticeable cons for nave bayes classification is that it is not good in handling unknown features as based on conditional probability and if a condition never appears before, it just gives very general prediction which may not be accurate. Random forest is a combinatorial classifier that develops various trees and classifies all trees based on votes. Multiple samples from initial samples are obtained using the Bootstrap resampling technique. A sub-dataset is created to shape and train the base decision tree. A class with the most votes from all the trees is allocated an object. For each sample, the algorithm chooses samples from the specified dataset first and then builds a decision tree. The outcomes of the forecast are calculated from each decision tree. To predict outcomes, a voting process is conducted. The most voted forecast is regarded as the class's final forecast. A convolutional neural network is a profound learning algorithm used to classify and recognize images. The CNN follows a hierarchical model that operates on the construction of a network like a funnel. It provides a fully linked layer that connects all the neurons and processes the output. The algorithm requires an input picture and assigns weights in the picture to different elements and is able to distinguish between them.

In order to learn particular patterns within the image, the convolution extracts the object's characteristics. It makes a network capable of recognizing the pattern in the image. Relu layer operates to add non-linearity in pictures at the end of the convolution operation by replacing all adverse values with zero. Next is the pooling layer that decreases the input image's dimensionality and decreases the complexity of the operating computation. This helps to avoid overfitting. In addition, a traditional neural network that links all neurons from the prior layer to the next layer is being built. At the end, the number on the input image is classified using a softmax activation function.

IV. PROPOSED WORK AND RESULT ANALYSIS

In this paper, the use of five distinct machine learning classifiers could identify three kinds of skin diseases called acne, lichen planus and sjs ten. For further classifications, the skin image dataset is originally preprocessed. The dataset is split into the dataset of instruction and testing: 80 percent for instruction and 20 percent for testing. The testing data is trained into three different classes denoted as class a, b and c for three diseases. Afterwards, skin diseases are detected using five different classification algorithms called machine learning, logistic regression, kernel SVM, naive bayes, random forest, and CNN. Each algorithm runs on the same dataset ten times and the training accuracy is calculated for each run. Skin diseases are detected afterwards using five different classification algorithms called machine learning, logistic regression, SVM kernel, naive bayes, random forest, and CNN. Each algorithm runs ten times on the same dataset and each run calculates the training precision. The parameters thus obtained are discussed and compared for all the five classification algorithms and graphical analysis is performed to check for the best algorithm which can be used for skin disease prediction. A brief overview and calculation formulas for different parameters are discussed below:

A confusion matrix is a prediction summary based upon the results obtained on a classification problem. It is a table that summarizes the number of correct and incorrect predictions. The matrix describes the performance of a classical model on a given dataset. It shows the errors being made by a classifier along with the type of errors that are being made. The true negatives (TN), true positives (TP), false negatives (FN) and false positives (FP) scores are stored in a matrix for each class. We have three distinct classes of skin disease called acne, lichen planus and sjs ten in the suggested skin surveillance scenario. In our proposed case scenario, the values in the cells are distributed as TN for each class of skin disease, results in which if the disease is absent, the model does not predict the disease.

TP, results in which when the disease is present the model properly predicts the disease. FN, results where the model predicts that the disease class is not present, but it is present. FP, results where the model mistakenly predicts the disease's presence, but this is not the case.

both of them. The F-Measure calculated will be close to the smaller value of Precision or Recall and is useful than accuracy, in case of uneven class distribution.

$$F\,1-\text{score} = (2 * (R * P\,))/((R + P\,)) \qquad (5)$$

Table-I : Confusion matrix

	class1(prediction)	class2(prediction)
class1(actual)	TP	FN
class2(actual)	FP	TN

Table-II: Confusion matrix for implemented classification algorithms on three classes of skin diseases

S.No.	Machine Learning Classifier	Testing Accuracy	Training Accuracy
1	Logistic Regression	68	73.76
2	Random Forest	67	73.36
3	Kernel SVM	50	50.7
4	Naive Bayes	47	49
5	CNN	96	99.05

Table- III: Precision, recall and F-1 score table for all five algorithms

	Logistic Regression			Random Forest			Kernel SVM			Gaussian NB			CNN		
	Acne	*Lichen Planus*	*Sjs Ten*	*Acne*	*Lichen Planus*	*Sjs Ten*	*Acne*	*Lichen Planus*	*Sjs Ten*	*Acne*	*Lichen Planus*	*Sjs Ten*	*Acne*	*Lichen Planus*	*Sjs Ten*
Acne	213	40	33	210	43	33	150	50	78	151	70	65	237	3	0
Lichen Planus	55	142	42	61	134	44	71	87	81	58	124	57	1	172	0
Sjs Ten	52	27	177	68	35	153	71	87	81	68	81	107	9	12	191

Table-IV: Testing accuracy and training accuracy in all five methods

S.No.	Machine Learning Classifier	Error Rate
1	Logistic Regression	0.32
2	Random Forest	0.33
3	Kernel SVM	0.50
4	Naive Bayes	0.53
5	CNN	0.04

Table-V: Training accuracy in all five methods

	Logistic Regression			Random Forest			Kernel SVM			Gaussian NB			CNN		
	P	R	F1-Score	P	R	F1-Score	P	R	F1-Score	P	R	F1-Score	P	R	F1-Score
Acne	0.67	0.74	0.70	0.62	0.73	0.67	0.51	0.55	0.55	0.55	0.53	0.54	0.96	0.99	0.97
Lichen Planus	0.68	0.59	0.63	0.63	0.56	0.59	0.51	0.36	0.43	0.45	0.52	0.43	0.92	0.99	0.97
Sjs Ten	0.70	0.69	0.70	0.67	0.60	0.63	0.48	0.57	0.52	0.47	0.42	0.44	1.0	0.95	0.95

Various parameters such as accuracy, recall accuracy, and F-score are calculated based on the information in the confusion matrix. Accuracy, also known as classification rate, can be de- scribed as right predictions of the overall results proportion. If the precision is greater, the skin disease is predicted properly. It is possible to calculate accuracy as:

$$A = (TP + TN\,)/((TP + TN + FP + FN\,)) \qquad (1)$$

Error rate can also be calculated by inverting the accuracy value as:

$$\text{Error Rate} = (1 - A) * 100 \qquad (2)$$

Recall, also called sensitivity is defined as the number of positive predictions divided by the number of positive class values in the test data. Higher Recall specifies the correct classification of skin disease. The recall is given by the following relation:

$$R = TP/(TP + FN\,) \qquad (3)$$

Precision is defined as the ratio of correctly predicted positive observations to the total predicted positive observations. Precision is given by the following relation:

$$P = TP/(TP + FP\,) \qquad (4)$$

The weighted average of Precision and Recall are calculated and results in F-measure. It represents a measurement for

Table II provides the confusion matrix for all five algorithms for each class of named skin diseases, acne, lichen planus and sjs ten. These matrices are also used to calculate the various parameters for each disease class such as precision(P), Recall'(R) and F1-score. Table III summarizes the calculated parameters. The calculated values of various parameters such as accuracy and error rates and accuracy of training are shown in Table IV and V. These parameter values are further analyzed by graphs and are displayed in Fig. 2 and Fig. 3.

As shown in table IV and V, we can conclude that CNN is giving the best training and testing accuracy of 99.05 % and 96 % respectively with the lowest error rate of 0.04. The analysis of graphs depicts that CNN provides more accurate prediction of skin diseases among all the five algorithms which results in less possibility of misdiagnosis. A better treatment can be initiated if the class of disease is predicted correctly at an early stage. CNN's multilayer perception property, which provides more precise classification outcomes, is the key behind this precision.

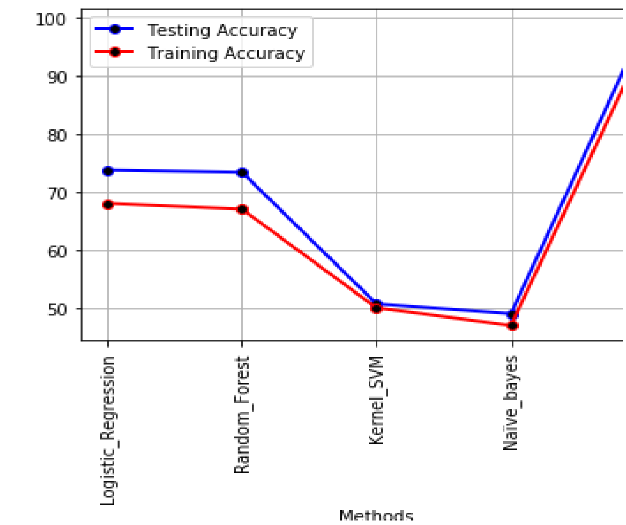

Fig. 2. Accuracy vs Methods

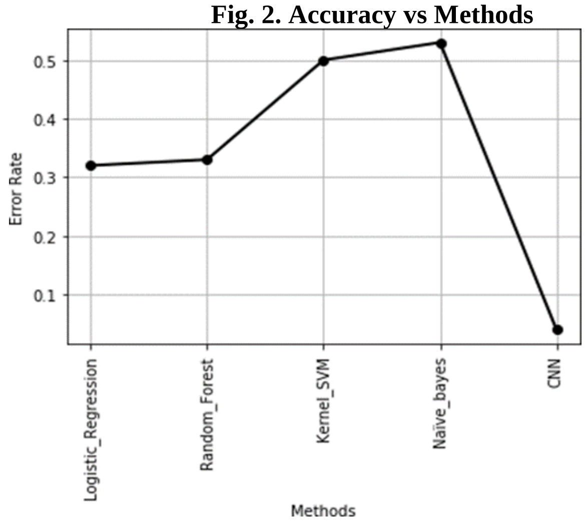

Fig. 3. Error Rate vs Methods

CNN is a fully linked neural feed-forward network consisting of several layers of unidirectional linked nodes, often trained by back propagation. This multi-layer architecture operates to extract, refine and classify prominent characteristics using various layers from a set of multidimensional input image datasets and provides more precise predictions.

V. CONCLUSION AND FUTURE SCOPE

Detection of skin disease is one of the major problems in the medical industry and can be healed and retrieved if properly diagnosed at an early point. Literature study demonstrates that different skin disease observation techniques are being used. However, there is still a great need to classify skin diseases at an early point. Machine learning algorithms have the potential to have an impact on early detection of skin diseases. It can assist people make real-time adjustments to their skin. If embraced well, the techniques will certainly provide appropriate assistance and a unified approach to skin problems prevention. This will assist patients and physicians cure skin diseases in a timely manner. Research and execution of limited medical information are accessible. If more real-time data are available in the future, the detection of skin disease can be explored with recent advances in AI and the benefits of diagnosis assisted with AI.

REFERENCES

1. Fikret Erc¸al, Madhav Moganti, William V Stoecker, and Randy H Moss. Detection of skin tumor boundaries in color images. IEEE Transactions on Medical Imaging, 12(3):624–626, 1993.
2. Sergey Demyanov, Rajib Chakravorty, Mani Abedini, Alan Halpern, and Rahil Garnavi. Classification of dermoscopy patterns using deep convo- lutional neural networks. In 2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI), pages 364–368. IEEE, 2016.
3. Harald Ganster, P Pinz, Reinhard Rohrer, Ernst Wildling, Michael Binder, and Harald Kittler. Automated melanoma recognition. IEEE transactions on medical imaging, 20(3):233–239, 2001.
4. Costantino Grana, Giovanni Pellacani, Rita Cucchiara, and Stefania Sei- denari. A new algorithm for border description of polarized light surface microscopic images of pigmented skin lesions. IEEE Transactions on Medical Imaging, 22(8):959–964, 2003.
5. Sigurdur Sigurdsson, Peter Alshede Philipsen, Lars Kai Hansen, Jan Larsen, Monika Gniadecka, and Hans-Christian Wulf. Detection of skin cancer by classification of raman spectra. IEEE transactions on biomedical engineering, 51(10):1784–1793, 2004.
6. Peter Aberg, Ingrid Nicander, Johan Hansson, Paul Geladi, Ulf Holm- gren, and Stig Ollmar. Skin cancer identification using multifrequency electrical impedance-a potential screening tool. IEEE transactions on biomedical engineering, 51(12):2097–2102, 2004.
7. Alexander Wong, Jacob Scharcanski, and Paul Fieguth. Automatic skin lesion segmentation via iterative stochastic region merging. IEEE Transactions on Information Technology in Biomedicine, 15(6):929–936, 2011.
8. Paul Wighton, Tim K Lee, Harvey Lui, David I McLean, and M Stella Atkins. Generalizing common tasks in automated skin lesion diag- nosis. IEEE Transactions on Information Technology in Biomedicine, 15(4):622–629, 2011.
9. M Emre Celebi, Quan Wen, Sae Hwang, Hitoshi Iyatomi, and Ger- ald Schaefer. Lesion border detection in dermoscopy images using ensembles of thresholding methods. Skin Research and Technology, 19(1):e252–e258, 2013.
10. Julia´n Oyola, Virginia Arroyo, Ana Ruedin, and Daniel Acevedo. Detection of chickenpox vesicles in digital images of skin lesions. In Iberoamerican Congress on Pattern Recognition, pages 583–590. Springer, 2012.
11. Do Hyun Chung and Guillermo Sapiro. Segmenting skin lesions with partial-differential-equations-based image processing algorithms. IEEE transactions on Medical Imaging, 19(7):763–767, 2000.
12. LS Zhong, Xin Jin, C Quan, Zhi-ping WEI, and Yan-qun LIU. Diag- nostic applicability of confocal laser scanning microscopy in psoriasis vulgaris. Chinese Journal of Dermatovenereology, 25(8):607–608, 2011.
13. R Sumithra, Mahamad Suhil, and DS Guru. Segmentation and classifi- cation of skin lesions for disease diagnosis. Procedia Computer Science, 45:76–85, 2015.
14. Juan Lu, Ed Kazmierczak, Jonathan H Manton, and Rodney Sinclair. Automatic segmentation of scaling in 2-d psoriasis skin images. IEEE transactions on medical imaging, 32(4):719–730, 2012.
15. S Salimi, M Sabbagh Nobarian, and S Rajebi. Skin disease images recognition based on classification methods. International Journal on Technical and Physical Problems of Engineering, 22(7):78–85, 2015.
16. S Kolkur, D Kalbande, P Shimpi, C Bapat, and J Jatakia. Human skin detection using rgb, hsv and ycbcr color models. arXiv preprint arXiv:1708.02694, 2017.
17. Abhijith L Kotian and K Deepa. Detection and classification of skin diseases by image analysis using matlab. International Journal of Emerging Research in Management andTechnology, 6(5):779–784, 2017.
18. Suneel Kumar and Ajit Singh. Image processing for recognition of skin diseases. International Journal of Computer Applications, 149(3):37–40, 2016.
19. Farzam Gorouhi, Parastoo Davari, and Nasim Fazel. Cutaneous and mucosal lichen planus: a comprehensive review of clinical subtypes, risk factors, diagnosis, and prognosis. The Scientific World Journal, 2014, 2014.
20. Robert A Schwartz, Patrick H McDonough, and Brian W Lee. Toxic epidermal necrolysis: Part i. introduction, history, classification, clinical features, systemic manifestations, etiology, and immunopathogenesis. Journal of the American Academy of Dermatology, 69(2):173–e1, 2013.

21. H Tigchelaar, N Kannikeswaran, and D Kamat. Stevens–johnson syndrome: An intriguing diagnosis. UBM Medica, 2008.
22. Siew-Kiang Tan and Yong-Kwang Tay. Profile and pattern of stevens-johnson syndrome and toxic epidermal necrolysis in a general hospital in singapore: treatment outcomes. Acta dermato-venereologica, 92(1):62–66, 2012.

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