Classification of skin diseases using machine learning techniques

[1]Rashid Ansari, [2]Sanjay Kadam, [3]Samadhan Sonavane

[1]PG Scholar, [3]Assistant Professor

[1]Sandip University, Nashik, India, [2]CDAC, Pune, India, [3]Sandip University, Nashik, India

Abstract: Automated classification of skin diseases is a challenging task. The main motivation for developing automated or semi-automated skin disease classification systems stems from the fact that experts for skin diagnosis may not be readily available in case of medical urgencies, especially in remote places. Also, due to the similarity in appearance of skin diseases, developing automatic skin disease classification systems becomes a necessity. Moreover, automated systems could serve as a supportive opinion in the diagnosis process. Hence, several attempts are being made to develop computer-aided diagnosis systems to classify skin diseases using lesion images of the corresponding skin diseases. In this paper, we present an overview of such attempts elaborating on various image processing and machine learning techniques used in developing such systems. This paper presents a comprehensive survey of various mechanisms used in the classification of skin diseases.

***Keywords*— skin disease, medical diagnose, image processing, machine learning, feature extraction, image classification**

I. Introduction

Skin diseases are fairly common infections across the globe. Patients with skin disorders face lot of hardships and pain due to skin disease deformations. Every year around 5.4 million new cases are being reported in the United States alone. Cutaneous malignancy is diagnosed in at least one in every five Americans during their lifetime. Approximately, about 75% of all skin cancer-related deaths in the US, which are over 10,000 deaths per year, are due to melanoma; even though they contribute only 5% of all skin cancer in the US. The survival chances of a patient with melanoma are over 99% if detected in the earlier stages, which drops to 14% when detected at later stages. Hence, early detection of skin disease is of prime importance [2].

Skin diseases are traditionally diagnosed by medical doctors by observing symptoms that indicate the disease that the patient is suffering from. However, due to the similarity in appearance of the skin disease patches the diagnosis could be subjective and at times can lead to the wrong diagnosis. The bias actually controls tests initiated by a medical specialist, so any search done by a human begins with keywords that are selected by the user. If a doctor starts checking symptoms that he/she feels most appropriate, then the order or weight given for any symptom may actually bias against the related diagnosis. In fact, there may be a symptom that may be given less significance and thus may not be included in the diagnosis.

Another motivation behind developing automated or semi-automated systems for skin disease classification is the fact that sometimes there is heavy dependence on medical specialists for medical diagnosis, especially in areas where specialists may not be readily available in case of medical urgency. The above problem requires a solution that can reduce dependency on medical experts. The solution is to develop a computer-aided diagnosis system, which classifies skin diseases. Also, there exists a lot of similarity in the appearance of skin diseases and therefore developing automatic skin disease classification systems has become a necessity. Moreover, automated systems could serve as a supportive opinion in the diagnosis process. Hence, several attempts are being made to develop computer-aided diagnosis systems to classify skin diseases using lesion images of the corresponding skin diseases, especially to ease diagnosis and treatment of skin patients living in remote areas.

Each type of skin disease has certain distinguishing characteristics. On the basis of these characteristics, classification is performed. The texture is an important feature that identifies the object present in an image. The texture is defined by the spatial distribution of pixels in the neighborhood of an image. Human engineered feature extraction is not suitable for a universal skin disease classification system. On one hand, hand-crafted features are usually dedicated to one or a limited number of skin diseases. They can hardly be applied to other classes and datasets. On the other hand, due to the diverse nature of skin diseases [40], human engineering for every skin disease is unrealistic. Feature learning can be used to overcome these issues. In feature learning, the machine is capable of choosing features and getting rid of feature engineering dependency [39]. In the past few years, various classification systems have been used for feature learning [7, 10, 13].

The paper is organized as follows. Section II elaborates on computer-aided diagnosis systems. Section III describes the techniques used in skin disease classification. Section IV gives a literature survey on the current efforts in developing automated or semi-automated skin disease classification systems. The last section gives conclusions of this survey.

II. Computer-aided diagnosis system

Computer-aided decision support tools are critical in medical imaging for diagnosis and evaluation. Predictive models are used in various types of medical domains for diagnostic and predictive functions. These models have been built on the basis of experience that constitutes the data obtained from real cases. Data can be pre-processed and converted to a set of rules comprising knowledge-base of an expert system, which can work as training data for machine learning models. The purpose of developing a CAD system for the diagnosis of skin diseases is to detect and determine the possibility of skin disease.

III. STEPS FOR SKIN DISEASES DETECTION

A) Using image processing techniques

Image processing is the use of a computer algorithm to improve the quality of a digital image and extract meaningful information.

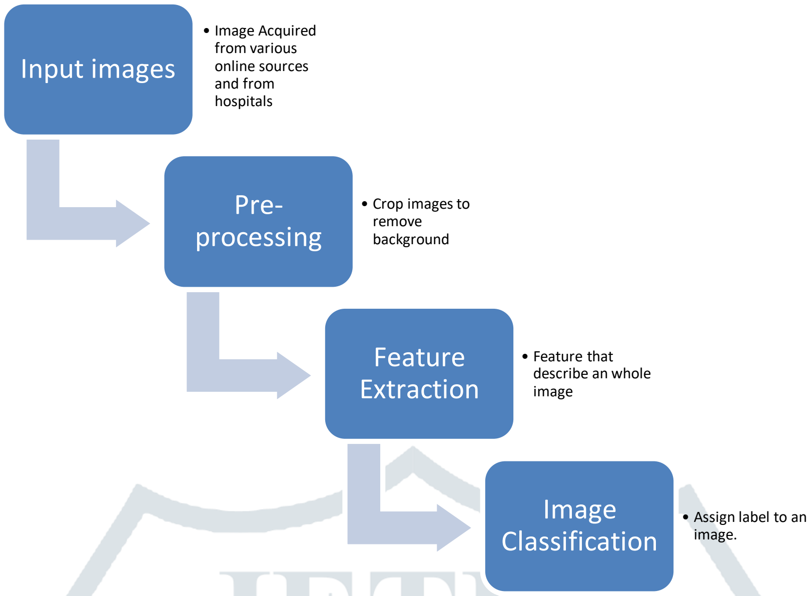

Fig 3.1 Steps in detecting skin diseases

1. Image preprocessing:

Image pre-processing is used to improve the image and remove unwanted distortions and enhance image features for further processing. For skin disease identification the legions of interests can be extracted manually by cropping an image or automated methods can be developed to do the same.

2. Feature Extraction:-

Feature extraction is used to extract meaningful information from the image. The features are unique properties that define an image. Features should contain the necessary information to differentiate between different image classes and should be insensitive to the irrelevant uncertainty in the input. The number of features should be limited to allow efficient training and classification.

Feature extraction techniques are described as follows:

2.1 Gray-level Co-occurrence matrix (GLCM)

GLCM is a matrix of different combinations of pixel brightness values (gray level) in an image [31]. GLCM texture thinks about the relation between the reference pixel and theneighbor pixel in an image. GLCM depicts the frequency of occurrence of pixels with specific values in a specified spatial relationship in an image, which is then followed by extracting statistical measures from this matrix, like homogeneity, correlation, symmetry, and energy, etc.

2.2 Hu Moments

It characterizes and quantifies the shape of an object in an image [32, 33]. Moments will extract the silhouette of an image. Moments are stable for translation, scale, and orientation, and are defined on geometric moments of images.

2.3 Gabor Filter

Gabor filter extract magnitude at different orientation and scales. A Gabor filter can be seen as a special frequency and a sign of a sinusoidal plane, which is modified by the Gaussian envelope [23]. Gabor filter is robust against image noise. Gabor features are directly extracted from grey-level images. The 2-D Gabor filter is given by:-

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \exp(i(2\pi \frac{x'}{\lambda} + \psi))$$

Where, $x' = x cos\theta + y sin\theta$

$$y' = -x sin\theta + y cos\theta$$

2.4 Histogram of Oriented Gradient (HOG)

In HOG, distribution of the direction of gradients is used as features. The gradient is useful because the magnitude of gradients is large around edges and corners [22]. The steps to calculate the HOG feature descriptor are as follows:

1) Make sure that the patches to be analyzed have a fixed aspect ratio.

2) To calculate HOG descriptor, we calculate the horizontal and vertical gradients. Also, we need to calculate the magnitude and direction of the gradient.

3) Image is divided into 8x8 cells and a histogram of gradients is calculated for every 8x8 cell. In these 8x8 cells histogram of gradients is created, which contains 9 bins corresponding to angles 0, 20, 40 … 160. After this, the image is normalized so that the gradient of image is independent of lighting variations.

2.5 Harris Corner

This is a mathematical operator that extract features in an image. It is easy to process and is quick enough to process on computers. It is prominent because it is independent of pivot, illumination and scale variation. This technique is used to extract corner features from the given image by using a mathematical form, which is [25]:

$$E(u,v) = \sum_{x,y} w(x,y)[I(x+u,y+v) - I(x,y)]^2$$

It finds the difference in intensity for a displacement of (u,v) in all directions.
$w(x,y)$ – represents windows functions
$[I(x+u,y+v)]$ – represents shifted intensity
$I(x,y)$ – is the Intensity

2.6 Shi-Tomasi Corner detection

These techniques performed better than Harris Corner detection by altering a little change in Harris Corner Detection. These techniques are based on Harris Corner Detection. The change is in the selection criteria for selection of the corner, which is calculating a score for each pixel and if the score is greater than a certain value, the pixel is represented as corner [26]. Shi-Tomasi proposed:- $R = \min(\lambda_1, \lambda_2)$
If R-value is above some threshold value then it represents a corner.

2.7 Scale-Invariant Feature Transform (SIFT)

SIFT features are obtained by applying gradient operations to images at various rotations and scales. SIFT attempts to find important points of interest, which are invariant to scale and orientation using a function called difference-of-Gaussian. Scale and location are determined by applying a model for all the candidate points. Now, orientations are cast to every key point [27]. By this, it helps in identifying unique features.

2.8 Speeded-Up Robust Features (SURF)

Problem with the SIFT is that the computation of Gaussian difference is expensive and comparatively slow [34]. So, SURF speed-up this process by calculating a Laplacian of Gaussian with Box Filter. By using this filter calculation of convolution becomes easy.

2.9 Features from Accelerated Segment Test (FAST)

Techniques that are discussed above like SIFT, SURF, Harris, Shi Tomasi generate good results but these techniques take significant computational time. FAST uses a 16 pixels circle to detect a corner. The corner can be detected by selecting threshold value t for particular point p having intensity Ip. If neighboring pixels under circle brighter than Ip + t or darker than Ip – t, then that point is taken as corner point [28].

2.10 Oriented FAST and rotated BRIEF

SIFT and SURF provide good performance in detecting keypoints but the problem with these two techniques is that they require high computation and these are patented. ORB is a combination of FAST keypoint detector and BRIEF (Binary Robust Independent Elementary Features) descriptor with many changes to improve the performance. It initializes with detecting keypoints using FAST, later using Harris corner detection to detect N points and after that, it uses rotated BRIEF for the descriptor [29].

2.11Segmentation-based Fractal Texture Analysis

Feature extraction through SFTA is done in two steps. In the first step, the input grayscale image is broken down into a set of binary images. For this purpose, two-threshold binary decomposition (TTBD) is used. In the second step, the fractal dimension is calculated from regions' boundaries of the outcome of each binary image [30]. The regions' boundaries of a binary image $I_b(x, y)$ are represented as a border image denoted by $\Delta(x, y)$ and computed as follow:

$$\Delta(x,y) = \begin{cases} 1 \; if \; \exists(x',y') \in N_S[(x,y)]: \\ \quad I_b(x',y') = 0 \; \wedge \\ \quad I_b(x,y) = 1 \\ 0 \;\; , otherwise \end{cases}$$

3. Image Classification

Image classification is a process of assigning a label to an input image from the available categories. There are different challenges for an algorithm to classify images, which are scale variation, intra-class variation, and background dislocation. The typical machine learning algorithms used comprise decision trees, random forests, Naïve-Bayes, and support vector machines (SVM). Although SVM is a binary classifier using a one-against-one approach, it can perform multi-class classification.

Various classification techniques are as follows:

3.1 Logistic Regression

It is best used when the target variable is absolute, although it can also be used for three or more categories with or without ordering [36]. Logistic regression uses a logistic function (sigmoid function), which gives output in the range [0, 1].

3.2 Naïve-Bayes

Naïve-Bayes classifier is probabilistic classifiers based on Bayes Theorem [37]. This technique is particularly favorable when the mobility of the inputs is high. For classification, it requires each feature of the given data set, where features individually help in classifying that data. Although this technique is fast it did not always produce better results for large data sets.

3.3 Stochastic Gradient Descent

SGB is used when the size of the training data is large [35]. SGB performs much better than the gradient descent when training data contains redundant data. It provides results to an optimization problem in less number of iterations. SGB is efficient in fitting linear models and its implementation is also easy but it is prone to feature scaling.

3.4 K-Nearest Neighbours (KNN)

KNN is a non-parametric technique, which does not provide presumption on given data [36]. It works on the basis of feature similarity, that is, features closely related to a given point. KNN is considered as a lazy technique, hence, it is used when one does not have previous knowledge about given data.

3.5 Decision Trees

Decision tree classifier creates a series of well-formed questions regarding characteristics of the dataset [36]. For every answer received, a follow-up question is asked, unless there are no conclusions about the call records label. This classifier maintains a tree structure for every question and condition. Data preparation requires fewer data and can be used on categorical as well as numerical data.

3.6 Random Forests

Random forest is made up of various decision trees over a sample of data, which is randomly selected [36]. It is an ensemble technique. Random forest performs well irrespective of missing values in the dataset. It reduces over-fitting and performs better than decision trees.

3.7 Support vector machine (SVM)

An SVM uses a hyperplane to separate given classes. It can produce appropriate accuracy and doesn't require much computation. It is simple to use and understand [36]. Although, SVM is binary classifier but to classify multiple classes it requires an approach, which is one-versus-one and one-versus-all. SVM is memory efficient and useful for handling higher-dimensional data.

B) Deep neural networks (DNNs)

A neural network consists of layered units (neurons) in layers, which maps an input vector to some output. It typically consists of an input layer, zero or more hidden layers, and an output layer. The neural network has learnable weights and biases, which adjust their value according to the current requirement. A deep neural network consists of various hidden layers with this layer it generates features depend on data [38].

Depending on the complexity of input data and desired output, the number of nodes (layers) also increases in the hidden layer. The layers in a deep neural network like convolution layers, pooling layers, and fully connected layers are used in combination to extract valuable features from an image [24].

Transfer learning is now widely used and can be applied to creating own user models. With transfer learning, one can use a pre-trained model.

C) Using deep neural networks:-

A neural network consists of layered units (neurons) in layers, which converts an input vector into some output. It consists of mainly three layers of input layers, hidden layers, and output layers. Hidden layers can be one or more than one. The neural network has learnable weights and biases which adjust their value according to the current requirement. A deep neural network consists of various hidden layers with this layer it generates features depend on data [38].

Depending on the complexity of input data and desired output increases, the number of nodes (layers) also increases in the hidden layer. Layers like convolution layers, pooling layers, max-pooling layer, fully connected layers [24]. All these layers used in combination to extract valuable features from an image.

Transfer learning is now widely used and can be applied to creating your own model. With transfer learning, you can use a pre-trained model. This model train over large data and you can apply over a little data.

IV. LITERATURE REVIEW

4.1 Skin detection through conventional methods

M. S. Manerkar et al. [1] developed an automated segmentation algorithm for different skin cancers. They have carried out pre-processing, contrast enhancement, RGB to L*a*b conversion and have applied C-means clustering and watershed algorithm for image segmentation. The feature extraction is performed using a Gray Level Co-occurrence matrix algorithm and Image Quality Assessment (IQA). Support Vector Machine algorithm has been used for the classification purpose. The results obtained by them shows that the C-means algorithm performs better (with an accuracy of 98%) as compared to the watershed algorithm (having an accuracy of 92%).

E. Kazmierczak et al. [2] have presented an algorithm that automatically segments scaling directly from skin and erythema in 2-D digital images. They have performed feature extraction of images using scaling contrast map and Gabor texture analysis. The scaling contrast map enhances the conspicuousness of scaling against erythema, and Gabor texture analysis differentiates between scaling and normal skin. The training sets are collected by the K-means algorithm to avoid human interferences. They have proposed a method, which is a semi-supervised scaling segmentation algorithm. The classification is performed using Support Vector Machine and Markov Random Field (MRF). Their proposed method performs better as compared to SVM and MRF.

S. M. Pereira et al. [5] have implemented feature extraction and selection methods for classification and analysis of the tissue composition of skin lesions or ulcers. The feature selection in image classification is very important and depends on the specific feature leading to an increase in accuracy. A database consisting of 172 dermatologic images has been prepared, the images being obtained from the School of Medicine of Ribeirao Preto, University of Sao Paulo. Each image was independently and manually segmented into two regions representing the lesion and the background by MACF.

Statistical measure got from co-occurrence matrices (CCMs) of the L*a*b and L*u*v color components gave preferable better classification result as compared to measures got from RGB and HSI color component. For the selection of features, the wrapper algorithm was chosen. The classifiers chosen to run the Wapper algorithm are the Naïve Bayes, multilayer perceptron (MLP), decision tree, and k-nearest-neighbor (KNN) methods.

Suganya R et al. [11] proposed a system to diagnose skin lesions detection and classification for dermoscopy images. They used K-means clustering for segmentation and color, texture and shape for feature extraction. The classification was performed using the support vector machine (SVM).

Md. Nazrul Islam et al. [12] classified skin diseases using image processing techniques. Maximum entropy thresholding method has been used for image segmentation. Feature extraction is performed using the GLCM algorithm. The proposed system consists of a feedforward multilayer network with backpropagation as a training model achieving an accuracy of 80%.

In the research work by O. G. Cula et al. [18] the skin viewed greatly affects its appearance. They capture a dependency of skin appearance on imaging parameters using bidirectional imaging. They construct a new skin texture database that contains bidirectional measurements of normal skin and skin affected by various disorders. To obtain bidirectional measurements they have used the polar and the azimuthal angles of the viewing direction, and the polar and the azimuthal angles of the illumination direction. They used Image textons and Symbolic texture primitives as features for classification.

R. Maurya et al. [19] proposed an automated system for detection and classification of skin into four types of skin cancers, that is, Melanoma, Basal cell carcinoma, Actinic Keratosis, and Squamous cell carcinoma. The features of skin lesions are extracted from each of the four classes using GLCM and for classification a multi-class support vector machine has been used. They achieved an accuracy of 81.43%

J. C. Kavitha et al. [20] have used image features comprising color, texture, shape and domain-specific aspects. They classify images into melanoma and non-melanoma. To extract the texture features of an image GLCM algorithm has been used, whereas, to extract the color features in three color spaces, which are RGB, HSV, and OPP, color histograms have been used. Support vector machine is used for the classification process. They have achieved an accuracy of 76 % for GLCM feature, 92% for RGB, 92% for HSV, 89% for OPP, and 93.1% for RGB + Texture.

4.2 Skin detection using deep learning

Yunchng Li et al. [6] investigated a useful approach for proper skin diagnosis. They have used Deep Neural Networks for classification. Using a dataset of 75,665 skin disease images from six publicly available dermatology atlantes, they train and compare both disease-targeted and lesion-targeted classifiers. For disease-targeted classification, only 27:6% top-1 accuracy and 57:9% top-5 accuracy has been achieved with a mean average precision (mAP) of 0:42.

Xavier Giro-i-Nieto et al. [7] develop a system, which can assist the human expert in making a better decision. The proposed solution is built around VGGNet convolutional neural network architecture. They trained the CNN from scratch, used the transfer learning paradigm to leverage features from VGGNet, keeping transfer learning paradigm and fine-tuning the CNN architecture. This is solved by using three methods training from scratch, ConvNet as feature extractor, Fine-tuning the ConvNet. They achieved an accuracy of M1-66.00%, m2-68.67%, M3-81.33%.

Yunhao et al. [8] have proposed computer-aided diagnosis system (CADs) for automatic segmentation and classification of melanoma lesions, containing a fully convolutional neural network (FCN) and a specific convolutional neural network (CNN). FCN, which consists of a 28-layer neural structure, is designed for segmentation and with a mask for a region of interest (ROI) as its output. Feature extracted with the CNN and DLCM feature is extracted. Combined features are used for classification which is done by CNN. They achieved an accuracy of 92%, a specificity of 93% and a sensitivity of 94%.

Zhang, Xinyuan et al [9] stated that a deep convolutional neural network (CNN) greatly improves the quality of computer-aided supporting systems. They used deep learning algorithms to diagnose four common cutaneous diseases. They achieved an accuracy of 87.25 +- 2.24% with test dataset of 1067 images.

Choi, JY et al. [10] have used a highly-efficient deep convolutional neural network. They classify the skin cancer using ECOC SVM, and deep convolutional neural network. The pre-trained AlexNet convolutional neural network model is used for extracting features. Their implementation results show that the maximum values for the average accuracy, sensitivity, and specificity are 95.1 (squamous cell carcinoma), 98.9 (actinic keratosis), 94.17 (squamous cell carcinoma), respectively. The minimum values of the average in these measures are 91.8 (basal cell carcinoma), 96.9 (Squamous cell carcinoma), and 90.74 (melanoma).

Esteva et al. [13] Deep CNN have potential to perform fine-grained object categorization. They trained CNN with images using only pixels and disease labels as inputs. Their result shows that CNN achieves performance on par with all tested experts. A CNN trained on a finer disease partition performs better than one trained directly on three or nine class. CNN learned internal features using t-SNE (t-distributed Stochastic Neighbor Embedding) and achieved an accuracy of 72.1%.

Hanging Zhou et al. [14] proposed a system for multi-classification using convolution neural networks (CNN). They classify six kinds of lesion disease including nevus, seborrheic keratosis, psoriasis, seborrheic dermatitis, eczema, and basal cell carcinoma. They achieved an accuracy of 65.8% for six-classification and 90% for a two-classification problem.

Y. Hasija et al. [15] suggest that if early diagnosis is done then disease can be cured and also with less cost. They also proposed an automated system of dermatological disease recognition. They used algorithms like Convolutional Neural Network and Support Vector Machine and amalgamated it with image processing tools to get an accuracy of 95.3%.

R. D. Putri et al. [16] have proposed a content-based image retrieval (CBIR) for skin disease identification and have used HSV-based color and GLCM-based features for the same. The similarity level of the image is measured by Euclidean Distance. They achieved a precision of 83.35% for HSV feature, 83.4% for GLCM feature and 80.94% for the combined features.

Zhang X et al. [21] elaborates on why is there a need for an automated image-based recognition system. They propose an automated image-based system for recognition of skin diseases using machine learning algorithms. Skin images are preprocessed to remove noise and are processed for enhancement of the image. The features are extracted using a Convolutional Neural Network (CNN) classifier based on the algorithm of softmax classifier.

Comparison of Table						
Work cited	Disease	Dataset	Features	Features Algorithm	Classifier	Results (Accuracy)
[1]	Benign, Malignant skin cancer and Warts	MIT BMI database	Contrast, Correlation, Energy, and Homogeneity, Mean Square Error, PSNR, SNR, Structural Content, Maximum Difference, Average Difference	GLCM and Image Quality Assessment	Support Vector Machine	>96% and 98%<
[2]	Psoriasis	722 psoriasis scaling images	edge and object detection, scaling contrast map	Scaling Contrast map and Gabor Texture	Markov Random Field and Support Vector Machine	Approx 74%
[5]	Skin Lesions	School of Medicine of Ribeirao Preto, University of Sao Paulo	Hue, saturation, L*u*v* and L*a*b* color	Color co-occurrence matrices	Wrapper algorithm, MLP, KNN, decision tree, Naïve Bayes	70.4
[6]	Skin disease nad skin lesion	Dermatology atlantes		CNN	Deep Neural Network	58
[7]	Melanoma, Benign	ISIC Archive dataset	Convolution Feature	VGGNet CNN	VGGNet CNN	M1-66.00%, m2-68.67%, M3-81.33%.
[9]	Melanocytic, psoriasis, seborrheic keratosis, basal cell carcinoma	Dermatology department of Peking Union Medical College Hospital.	Convolutional feature,	CNN	GoogleNet Inception v3	87.25
[10]	Skin cancer	Dermnet	Convolutional feature,	AlexNet convolutional neural network	ECOC SVM and deep convolutional neural network	95.1
[11]	Melanoma, Nevus, BCC and Seborrhoeic Keratosis	Dermweb	Color, sub-region, skewness, mean and Standard deviation, text, shape	--	Support Vector Machine	96.8
[12]	Eczema, Impetigo, and Psoriasis	Dermnet	contrast, correlation, homogeneity, energy,	GLCM	Backpropagation Neural Network (BPN)	80

[13]	Skin disease	129,450 skin lesions comprising 2,032 different diseases.	Convolutional features	GoogleNet Inception v3 CNN	GoogleNet Inception v3 CNN	3 class disease partition-72.1,9 class disease partition–5.4
[14]	Nevus, seborrheic keratosis, psoriasis, seborrheic dermatitis, eczema, BCC	Department of Dermatology, Peking Union Medical College Hospital,	Convolution features	CNN	CNN	six-classification 65.8 and two classification 90
[15]	Eczema, Herpes, Melanoma, and Psoriasis	Dermatology online websites	Convolutional features	CNN	SVM	95.3
[19]	Melanoma, BCC, actinic Keratosis, Squamous cell carcinoma	Dermnet	entropy, contrast, correlation, homogeneity, energy, RGB, HSV, and OPP	GLCM	Multi-class SVM	81.43
[20]	Melanoma	Dermatology online websites	entropy, contrast, correlation, homogeneity, energy, RGB, HSV, and OPP	GLCM, Color histogram	SVM	
[21]	Five skin disease	Dermnet	Convolutional feature	CNN	CNN Softmax classifier	Approx 70

Table 4.1 Comparison Table

V. CONCLUSION

Based on the survey done, it can be concluded that deep neural networks though very effective and precise have not substituted the conventional machine techniques for skin disease classification as deep learning needs a large amount of data for better performance. The conventional techniques usually perform better for smaller training data sets. In some cases, conventional techniques give better and effective output as deep learning methods overkill the task. Deep learning requires a high-performance system and require a large amount of time to train a model. The conventional techniques perform better and require lesser lines of code as compared to deep learning models. Preprocessing steps in deep learning can be better understood by learning conventional and this, in turn, helps the performance of deep learning techniques. However, if the goal is to achieve better accuracy and if larger training data set is easily available, with inadequate knowledge of feature introspection, then deep learning technology appears to perform better in comparison to other techniques.

VI. REFERENCES

[1]. M. S. Manerkar, U. Snekhalatha, S. Harsh, J. Saxena, S. P. Sarma, and M. Anburajan, "Automated skin disease segmentation and classification using multi-class SVM classifier," 3rd International Conference on Electrical, Electronics, Engineering Trends, Communication, Optimization and Sciences (EEECOS 2016), Tadepalligudem, 2016, pp. 1-6.
doi: 10.1049/cp.2016.1528

[2]. J. Lu, E. Kazmierczak, J. H. Manton and R. Sinclair, "Automatic Segmentation of Scaling in 2-D Psoriasis Skin Images," in IEEE Transactions on Medical Imaging, vol. 32, no. 4, pp. 719-730, April 2013.
doi: 10.1109/TMI.2012.2236349

[3]. R. Parekh, "Using Texture Analysis for Medical Diagnosis," in IEEE MultiMedia, vol. 19, no. 2, pp. 28-37, Feb. 2012.
doi: 10.1109/MMUL.2010.88

[4]. Y. Lei, W. Yuan, H. Wang, Y. Wenhu and W. Bo, "A Skin Segmentation Algorithm Based on Stacked Autoencoders," in IEEE Transactions on Multimedia, vol. 19, no. 4, pp. 740-749, April 2017.
doi: 10.1109/TMM.2016.2638204

[5]. S. M. Pereira, M. A. C. Frade, R. M. Rangayyan and P. M. Azevedo-Marques, "Classification of Color Images of Dermatological Ulcers," in IEEE Journal of Biomedical and Health Informatics, vol. 17, no. 1, pp. 136-142, Jan. 2013.
doi: 10.1109/TITB.2012.2227493

[6]. Haofu Liao, Yuncheng Li and Jiebo Luo, "Skin disease classification versus skin lesion characterization: Achieving robust diagnosis using multi-label deep neural networks," 2016 23rd International Conference on Pattern Recognition (ICPR), Cancun, 2016, pp. 355-360.

[7]. A. Romero Lopez, X. Giro-i-Nieto, J. Burdick and O. Marques, "Skin lesion classification from dermoscopic images using deep learning techniques," 2017 13th IASTED International Conference on Biomedical Engineering (BioMed), Innsbruck, Austria, 2017, pp. 49-54.doi: 10.2316/P.2017.852-053

[8]. Yunhao Ge, Bin Li, Yanzheng Zhao, Enguang Guan, and Weixin Yan. 2018. Melanoma Segmentation and Classification in Clinical Images Using Deep Learning. In Proceedings of the 2018 10th International Conference on Machine Learning and Computing (ICMLC 2018). ACM, New York, NY, USA, 252-256. DOI: https://doi.org/10.1145/3195106.3195164

[9]. TY - JOURAU - Zhang, XinyuanAU - Wang, ShiqiAU - Liu, JieAU - Tao, CuiPY - 2018DA - 2018/07/23TI - Towards improving diagnosis of skin diseases by combining deep neural network and human knowledge

[10]. Dorj, UO., Lee, KK., Choi, JY. et al. Multimed Tools Appl (2018) 77: 9909. https://doi.org/10.1007/s11042-018-5714-1

[11]. R. Suganya, "An automated computer aided diagnosis of skin lesions detection and classification for dermoscopy images," 2016 International Conference on Recent Trends in Information Technology (ICRTIT), Chennai, 2016, pp. 1-5.
doi: 10.1109/ICRTIT.2016.7569538

[12]. M. N. Islam, J. Gallardo-Alvarado, M. Abu, N. A. Salman, S. P. Rengan and S. Said, "Skin disease recognition using texture analysis," 2017 IEEE 8th Control and System Graduate Research Colloquium (ICSGRC), Shah Alam, 2017, pp. 144-148.
doi: 10.1109/ICSGRC.2017.8070584

[13]. JOUR, Esteva, Andre, Kuprel, Brett, Novoa, Roberto A., Ko, Justin, Swetter, Susan M., Blau, Helen M., Thrun, Sebastian "Dermatologist-level classification of skin cancer with deep neural networks" Nature 2017/01/25/online 542 115 Macmillan Publishers Limited, part of Springer Nature. All rights reserved. https://doi.org/10.1038/nature21056 10.1038/nature21056

[14]. H. Zhou, F. Xie, Z. Jiang, J. Liu, S. Wang and C. Zhu, "Multi-classification of skin diseases for dermoscopy images using deep learning," 2017 IEEE International Conference on Imaging Systems and Techniques (IST), Beijing, 2017, pp. 1-5.
doi: 10.1109/IST.2017.8261543

[15]. Y. Hasija, N. Garg and S. Sourav, "Automated detection of dermatological disorders through image-processing and machine learning," 2017 International Conference on Intelligent Sustainable Systems (ICISS), Palladam, 2017, pp. 1047-1051.

[16]. R. D. Putri, H. W. Prabawa and Y. Wihardi, "Color and texture features extraction on content-based image retrieval," 2017 3rd International Conference on Science in Information Technology (ICSITech), Bandung, 2017, pp. 711-715.
doi: 10.1109/ICSITech.2017.8257205

[17]. S. Routray, A. K. Ray and C. Mishra, "Analysis of various image feature extraction methods against noisy image: SIFT, SURF and HOG," 2017 Second International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, 2017, pp. 1-5.
doi: 10.1109/ICECCT.2017.8117846

[18]. O. G. Cula, K. J. Dana, F. P. Murphy and B. K. Rao, "Bidirectional imaging and modeling of skin texture," in IEEE Transactions on Biomedical Engineering, vol. 51, no. 12, pp. 2148-2159, Dec. 2004.doi: 10.1109/TBME.2004.836520

[19]. R. Maurya, Surya Kant Singh, A. K. Maurya and A. Kumar, "GLCM and Multi Class Support vector machine based automated skin cancer classification," 2014 International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, 2014, pp. 444-447.

[20]. J. C. Kavitha and A. Suruliandi, "Texture and color feature extraction for classification of melanoma using SVM," 2016 International Conference on Computing Technologies and Intelligent Data Engineering (ICCTIDE'16), Kovilpatti, 2016, pp. 1-6.doi: 10.1109/ICCTIDE.2016.7725347

[21]. Zhang X, Wang S, Liu J, Tao C. Towards improving diagnosis of skin diseases by combining deep neural network and human knowledge. BMC Med Inform Decis Mak. 2018;18(Suppl 2):59. Published 2018 Jul 23. doi:10.1186/s12911-018-0631-9

[22]. N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), San Diego, CA, USA, 2005, pp. 886-893 vol. 1.
doi: 10.1109/CVPR.2005.177

[23]. A. Jain and S. Bhattacharjee, ``Address block location on envelopes using gabor filters," vol. 25, no. 12, 1992.

[24]. Christian S. Perone (19/08/2015 CNN & feature extraction) Retrieved from http://blog.christianperone.com/2015/08/convolutional-neural-networks-and-feature-extraction-with-python.

[25]. Harris, Chris, and Mike Stephens. "A combined corner and edge detector." Alvey vision conference. Vol. 15. No. 50. 1988.

[26]. Jianbo Shi and Tomasi, "Good features to track," 1994 Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, Seattle, WA, USA, 1994, pp. 593-600.

[27]. Lowe, David G. "Distinctive image features from scale-invariant keypoints." International journal of computer vision60.2 (2004): 91-110.

[28]. Rosten, Edward, and Tom Drummond. "Machine learning for high-speed corner detection." European conference on computer vision. Springer, Berlin, Heidelberg, 2006.

[29]. Rublee, Ethan, et al. "ORB: An efficient alternative to SIFT or SURF." Computer Vision (ICCV), 2011 IEEE international conference on. IEEE, 2011.

[30]. Costa, Alceu Ferraz, Gabriel Humpire-Mamani, and Agma Juci Machado Traina. "An efficient algorithm for fractal analysis of textures." Graphics, Patterns and Images (SIBGRAPI), 2012 25th SIBGRAPI Conference on. IEEE, 2012.

[31]. Robert M Haralick; K Shanmugam; Its'hak Dinstein (1973). "Textural Features for Image Classification" (PDF). IEEE Transactions on Systems, Man, and Cybernetics. SMC-3 (6): 610–621.

[32]. M. K. Hu, "Visual Pattern Recognition by Moment Invariants", IRE Trans. Info. Theory, vol. IT-8, pp.179–187, 1962

[33].http://docs.opencv.org/modules/imgproc/doc/structural_analysis_and_shape_descriptors.html?highlight=cvmatchshapes#humoments Hu Moments' OpenCV method

[34]. Herbert Bay, Andreas Ess, Tinne Tuytelaars, and Luc Van Gool, "Speeded Up Robust Features", ETH Zurich, Katholieke Universiteit Leuven.

[35]. Bottou, Léon (2004), "Stochastic Learning", Advanced Lectures on Machine Learning, LNAI, 3176, Springer, pp. 146–168, ISBN 978-3-540-23122-6.

[36]. James, Gareth, et al. An introduction to statistical learning. Vol. 112. New York: springer, 2013.

[37]. Webb, G. I.; Boughton, J.; Wang, Z. (2005). "Not So Naive Bayes: Aggregating One-Dependence Estimators". Machine Learning. Springer. 58 (1): 5–24. doi:10.1007/s10994-005-4258-6

[38]. Schmidhuber, J. (2015). "Deep Learning in Neural Networks: An Overview". Neural Networks. 61: 85–117. arXiv:1404.7828. doi:10.1016/j.neunet.2014.09.003. PMID 25462637

[39]. Y. Bengio, A. Courville, and P. Vincent. Representation learning: A review and new perspectives. IEEE Trans. Pattern Anal. Mach. Intell., 35(8):1798–1828, Aug. 2013.

[40]. N. Cox and I. Coulson. Diagnosis of skin disease. Rook's Textbook of Dermatology, 7th edn. Oxford: Blackwell Science,5, 2004.