Microprocessors and Microsystems 76 (2020) 103074

Contents lists available at ScienceDirect

Microprocessors and Microsystems

journal homepage: www.elsevier.com/locate/micpro

Automatic diagnosis of skin diseases using convolution neural network

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ARTICLE INFO

Article history:
Received 6 January 2020
Revised 26 February 2020
Accepted 2 March 2020
Available online 19 March 2020

Keywords:
Skin disease
Detection
Convolution neural network
AlexNET
Pooling
Convolution layer

ABSTRACT

Skin diseases are becoming a most common health issues among all the countries worldwide. The method proposed in this work detects four types of skin diseases using computer vision. The proposed approach involves Convolutional Neural Networks with specific focus on skin disease. The Convolutional Neural Network (CNN) used in this paper has utilized around 11 layers viz., Convolution Layer, Activation Layer, Pooling Layer, Fully Connected Layer and Soft-Max Classifier. Images from the DermNet database are used for validating the architecture. The database comprises all types of skin diseases out of which we have considered four different types of skin diseases like Acne, Keratosis, Eczema herpeticum, Urticaria with each class containing around 30 to 60 different samples. The challenges in automating the process includes the variation of skin tones, location of the disease, specifications of the image acquisition system etc., The proposed CNN Classifier results in an accuracy of 98.6% to 99.04%.

1. Introduction

In recent years, intervention of computers in all fields is inevitable. Medical field is one such field which depends on computers to a greater extent for diagnostic purpose. Involving machines for diagnosis aids the physicians to address more patients and helps in diagnosis with minimum errors. The proposed work aims at recognising and classifying skin diseases present in human body using image processing technique. In this paper, we extracted the different skin disease images in DermNet database and classify the diseases by using convolutional neural network architecture. The major skin diseases like acne, keratosis, Eczema herpeticum, and Urticaria are taken into consideration and in this paper a deep learning is proposed for automatic grouping of these diseases. The rest of the proposed work is organised as followed. Subdivision II discusses about the recent works in the area of CNN and detection of skin diseases. Subdivision III elaborates the proposed work in detail. Subdivision IV deals with the description of dataset used to validate the proposed system. Subdivision V provides the results and discussion. Finally, conclusion is provided in subdivision VI.

2. Literature survey

Skin disease images have vast variations in the texture of the image; several authors have attempted to design an automatic detection system based on the texture features.

In [3] A.C. Bovik et. al. has proposed a method that employs 2-D Gabor filters to localise spatial variations in orientation, phase or frequency of the textures. Gabor phase responses were used as information to spot discontinuities in phase in the visible texture. Haralick in [4] have adopted the numerical and structural method using symmetric Grey Level Co-occurrence Matrix (GLCM) to model texture-based patterns. The occurrence of the gray tone in the neighbourhood at a specific distance and specific direction is obtained from the GLCM matrix. The texture features like contrast; coarseness and directionality were calculated by Tamura et al in [10]. Contrast measures the vibrancy of the texture pattern affected using varying intensities. The average region of the image with same intensity or granulation of an image is indicated as coarseness. The distributions of the grey values in a specific direction within the image are represented as directionality. Anal Kumar Mittra et al in [4] adopted Hough transform along with directional histogram to measure the directionality. A high degree of correlation between human estimates of roughness and fractal dimensions was reported in [5] by Pentland et al.

J.M. Blackledge et al in [2] have adopted a method that involves lacunarity and fractal dimensions as fractal parameters to detect and recognize skin cancers. Rubegni et al in [6] have suggested a

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https://doi.org/10.1016/j.micpro.2020.103074
0141-9331/

method to analyse dermoscopy image and to detect the pigmented skin lesions. Smach et al in [7] employed a technique for face detection using skin colour, skin texture and shape features along with MLP neural network classifier

Esteva et al in [8] have proposed a deep neural network for categorising images of skin cancer. A pretrained Google inception V3 CNN architecture is fine-tuned with dataset of 129,450 images with 2032 classes of skin diseases. The algorithm is validated with three class diseases such as non-neo plastic lesions, malignant lesions and benign lesions. The CNN achieves 72.1% of average accuracy for three class classification and 55.4% of accuracy for nine class classification. In [9] N.C.F.Codella et al have proposed a system that combines the machine learning approaches for detecting melanoma by analysing the segmented skin lesions [8]. Various features like color histogram, edge histogram and multiscale variant LBP features were computed from a pair of images in which one contains the whole image and other is from the cropped portion of the image containing the lesion. These features were used to train the nonlinear SVM for classification. A publicly available ISBI 2016 challenge dataset with 1279 images were used for validating the system. The system was trained with 70% of the images and performance of the system was tested using the remaining 30% of the images. The proposed system achieves accuracy of 76% with sensitivity and specificity of 82% and 62% respectively. In [10] Shanthi et al have classified diabetic retinopathy (DR) images by using a modified Alexnet architecture. DR images were classified into four classes like images of healthy retina, DR stage1, DR stage2 and DR stage3. Messidor dataset images were used for validating the network and the proposed method achieved a maximum classification accuracy of 96.6% for the classes of images in diabetic retinopathy stage1 and diabetic retinopathy stage3.

In [11] Lekkas et al have obtained an improvement in classification accuracy of 4.05% for Pima Indians diabetes (PID) dataset and 4.85% for DERM dataset. With respect to PID dataset needs a binary classification problem and DERM dataset needs the classification of skin diseases like chronic dermatitis, psoriasis, lichen planus, pityriasis rubra pilaris, pityriasis rosea and seboreic dermatitis. Phung et al in [12] developed an algorithm for detecting skin portions in the given image by combining histogram technique with the Bayesian classifier and multilayer perceptron classifier. The algorithm outperforms other classifiers like three unimodal Gaussian classifiers, three piecewise linear classifiers and a Gaussian mixture classifier. The proposed method performs better because of the larger training set created with features having lower dimensions.

Ranjan Parekh in [23] has proposed a method for detecting three types of skin ailments by using the texture related features. The method is tested with dataset from dermnet .com. Features from wavelet decomposition matrix (WDM) and Gray Level co-occurrence matrix (GLCM) are fed to the neural network classifier for classifying the skin diseases. The author has taken three specific classes of skin diseases like eczema (Class E), Acne (Class A) and utricaria (class U), with each class having 230 images for testing the performance of the proposed system. Out of 690 images around 47% of images were used for training and remaining 53% of images were used for testing the classifier. The system computed five GLCM features like contrast, homogeneity, mean, energy and variance. Three different types of features were selected. Initially the system is evaluated with individual features, then with combination of features (combination of GLCM features or combination of WDM features) and finally hybrid features (combination of GLCM features with WDM features).Among the individual features, GLCM homogeneity and first three levels of WDM produced the best recognition rates of approximately 82.5% and 64.75% respectively. The joint feature HM produced the result of 83.1%.

Mariam A.Sheha et al, in [24] have recommended a method to detect melanoma for a set of dermoscopy images. The system is used to classify the images either as malignant melanoma or melanocytic nevi based on GLCM features and using multilayer perception (MLP) classifier. Based on Fisher score, dominant features such as cluster prominence, correlation, contrast, dissimilarity, difference variance, homogeneity were selected for further processing. The author has tested the performance with a traditional MLP and an automatic MLP. Traditional MLP outperformed the automatic MLP with training and testing accuracy of 100% and 92 % respectively.

H.Tushabe et al in [28] have suggested a method to detect skin disorders and to classify them as virus infections or bacterial infections. From three different districts of Uganda 127 sample skin images were collected for evaluating the proposed method. Features based on color distribution of images and scale invariant feature transformation (SIFT) interest points were adopted in the method proposed by the author. Classification was done by different classifiers like 2-norm support vector classifies (SVC), two-layer perceptron neural network (NN), naïve Bayes (NB), and k-nearest neighbour classifier (KNN). A classifying accuracy of 100% is achieved for KNN classifier and the second-best result of 92% classification accuracy was achieved for SVC. As there is not much variation in the color of the infected part of the skin in both class of diseases, SIFT features produced better performance than HSV extracted feature set.

3. Proposed method

The proposed work aims to detect and categorize different skin diseases in human body using AlexNet Architecture [1]. Fig. 1 displays the architecture for our proposed work.

Convolutional Neural Network Architecture [25,26] have several layers like Fully Connected layer pooling layer, convolution layer, Rectified Linear Unit layer, which are discussed in the following subsections.

3.1. Convolution layer

The convolution layer consists of neurons that connect to small area of the input image [13] called as filters or masks. Filter size are specified like [3 × 3, 5 × 5, 7 × 7, etc.]. The number of weights used to the filter is [h × w × c], where '*h*' is the height of an image, '*w*' is the width of an image and '*c*' is the depth of an image. The total number of parameters in a convolution layer is computed using Eq. (1) and the output size of convolution layer size can be predicted using Eq. (2) and the Fig. 2 describes general two dimensional convolution operations functions in convolution neural networks [17–19].

$$\text{Total Parameters} = (h \times w \times c) + 1 \tag{1}$$

$$\text{Size of Convolution layer O/p} = \frac{\{\text{I/p Image size} - \text{Filter size} + 2* \text{Padding}\}}{\text{Stride}} + 1 \tag{2}$$

Where the number of pixels skipped while moving the filter in vertical and horizontal direction is denoted as" Stride" and the number of zeros added in image for corner pixels and pixel in the edges are represented as" Padding" . The proposed work considers inputs of size [227 × 227] for feeding the AlexNet architecture.

3.2. Rectified linear unit layer (ReLU)

This layer performs thresholding operation to the entire image. This layer retains the positive values and all the negative values

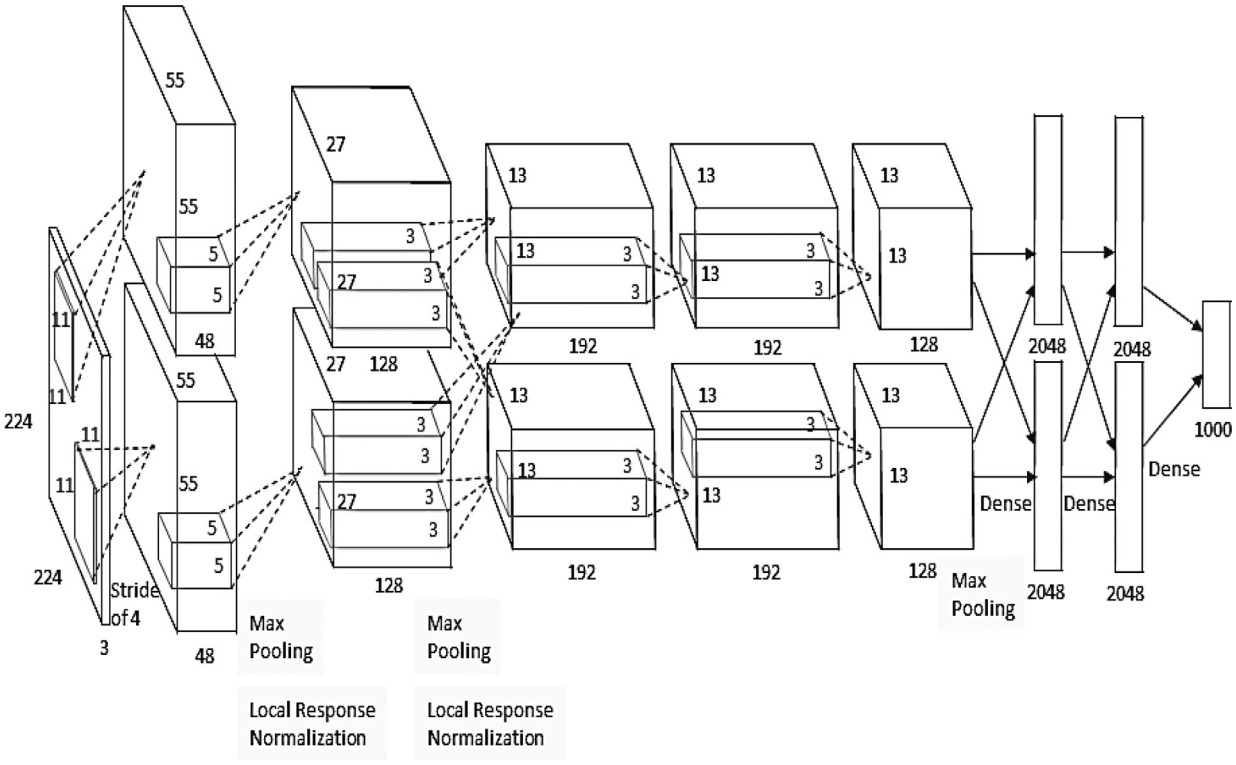

Fig. 1. AlexNET CNN Architecture

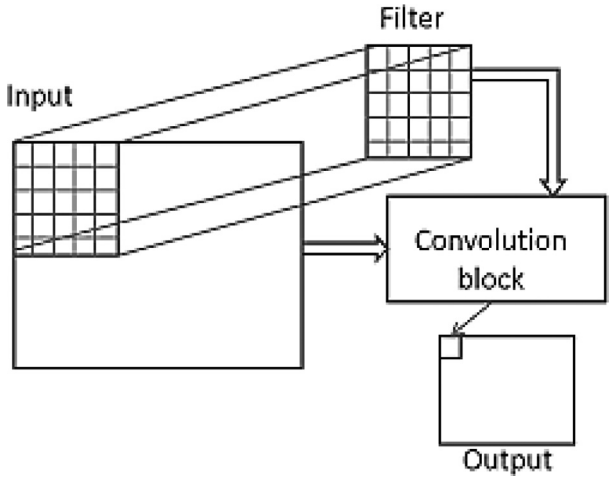

Fig. 2. Basic two-dimensional Convolution Operations

are replaced with zero. Output of ReLU layer can be computed using Eq. (3). This eliminates the unwanted pixels in an image $i(h, w)$. The Fig. 3 describes general activations functions in convolution neural networks [22].

$$output\ \ of\ ReLU\ \ Layer\ \ i(h,w) = \begin{cases} i(h,w) & i(h,w) \geq 0 \\ 0 & i(h,w) < 0 \end{cases} \quad (3)$$

3.3. Pooling layer

The output of ReLU layer is fed to Pooling layer. Average pooling or Maximum Pooling can be performed. The input image is segregated into small patches either rectangular or square of equal size. The pooling layer outputs either the average value or maximum value in each patch of the given input. This considerably downsizes the given input which is shown in Fig. 4 [20],[21].

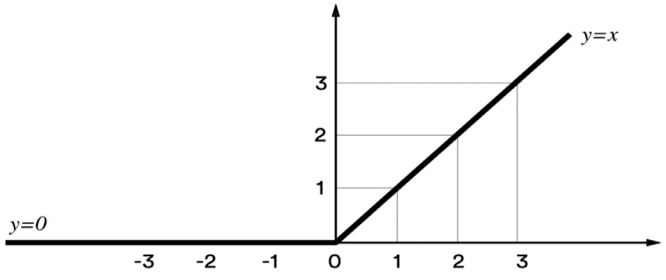

Fig. 3. Rectified Linear Unit Layer (Activation Function)

3.4. Fully connected layer

The final fully connected layer multiples the output from the preceding layer by a kernel matrix with weights and then bias vector added to it. The proposed work aims at categorizing the input image into four classes like acne, keratosis, eczema herpeticum, and urticaria (classes) & which is shown in Fig. 5 [23].

4. Dataset description

The work recommended in this paper is to classify skin diseases using convolution neural network. Sample images for the diseases like acne, keratosis, Eczema herpeticum, and Urticaria from DermNet dataset are considered for validating the network. The 174 images acquired from the dataset are split into two, training phase involves 105 images and testing phase uses 69 images. The Table 1 & Fig. 6 displays the distribution of the images in various classes. Fig. 7 shows the sample images for different skin diseases is used in this work. Descriptions

The general flow of our proposed method is shown in Fig. 8. Totally, 4 different classes like Acne, keratosis, Eczema herpeticum, and Urticaria are classified using CNN architecture. To assessment

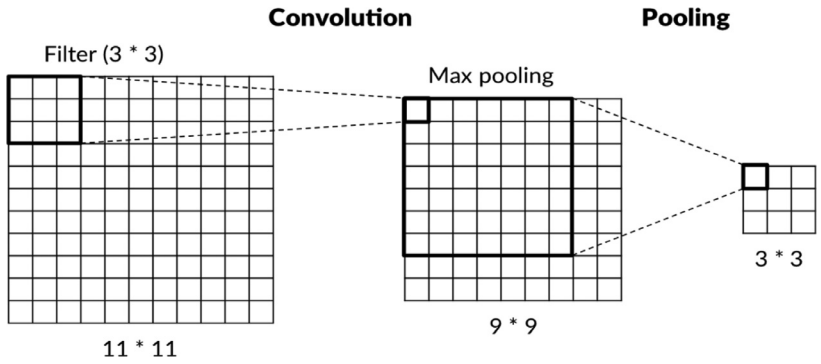

Fig. 4. Maximum Pooling Operations

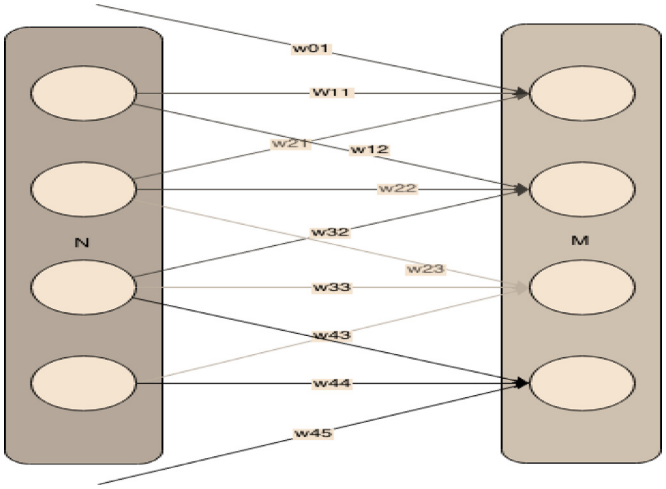

Fig. 5. Fully Connected CNN Layer

Table 1
Distribution of the images in various classes of skin diseases.

Skin disease	Training samples	Testing samples	Total samples
Acne	27	14	41
Keratosis	40	26	66
Eczema herpeticum	21	15	36
Urticaria	17	14	31
Total	105	69	174

the performance of our idea we analyzed experimentation on skin diseases images and we formed our own data base segmentation method. This database has 5 folders and entirely training and validate database and testing database are 117 & 76 different skin diseases which is used to make for creating model for testing.

5. Results and discussions

The proposed architecture was trained with 105 images from the DermNet database and performance of the proposed architecture was tested with 69 images. The convolutional neural network (AlexNet) takes 1000 epochs (1,00,000 Iterations) in two or three days to train the network. Stochastic Gradient Method (Eq. 4) has a hyper tuning parameter (learning(ε) rate 0.01; momentum 0.9 and weight decay 0.005 are used in this model and $\langle \frac{\partial L}{\partial w} \rangle$ is gradient loss.

$$v_{i+1} = 0.9 * v_i - \left(0.05 * \varepsilon * w_i - \varepsilon * \left\langle \frac{\partial L}{\partial w} \right\rangle\right) \tag{4}$$

Several Convolutional filters (kernels) are used to extract features in a 2-D image. In each convolutional layer, number of filters with the same dimensions is used. For instance, the primary convolutional Layer [25] of AlexNet contains 96 filters of size 11 × 11 × 3 [14–16]. Note the thickness and altitude of the filters are typically the similar and the deepness is the similar as the number of networks. The first 2 Convolutional layers are tailed by the overlying maximum pooling layer. The 3rd, 4th, 5th convolutional layers are linked directly. The 5th convolutional layer is tailed by an overlying maximum pooling layer, the result of which goes into a sequence of completely connected dual networks. The additional fully connected convolution layer feeds into

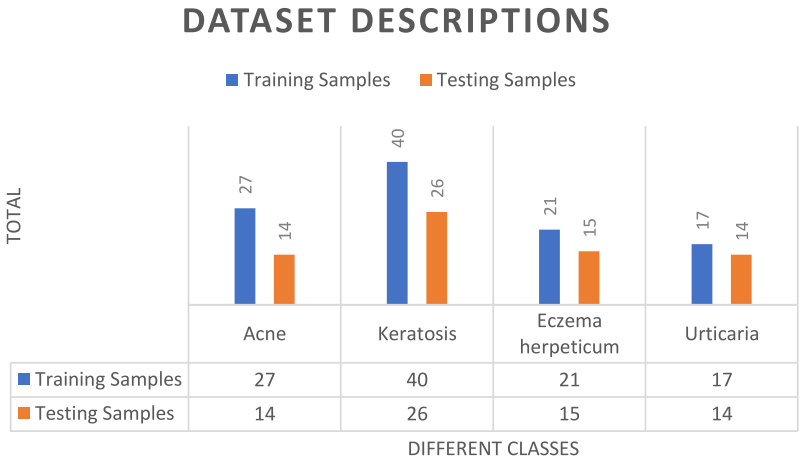

Fig. 6. Dataset Descriptions for Skin Disease Detection

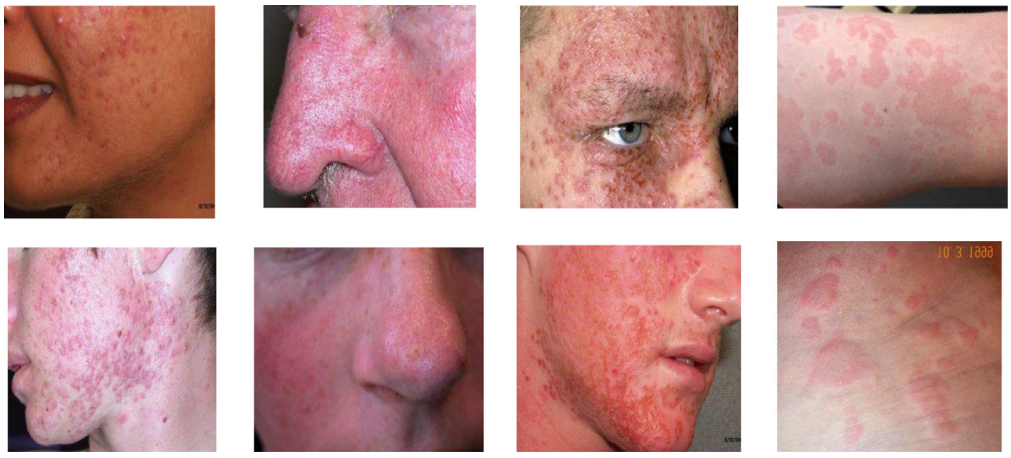

Fig. 7. sample images from each class

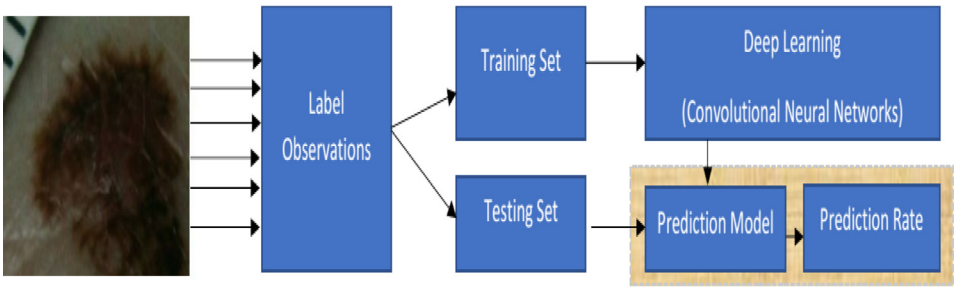

Fig. 8. General Flow Diagram for Proposed Method

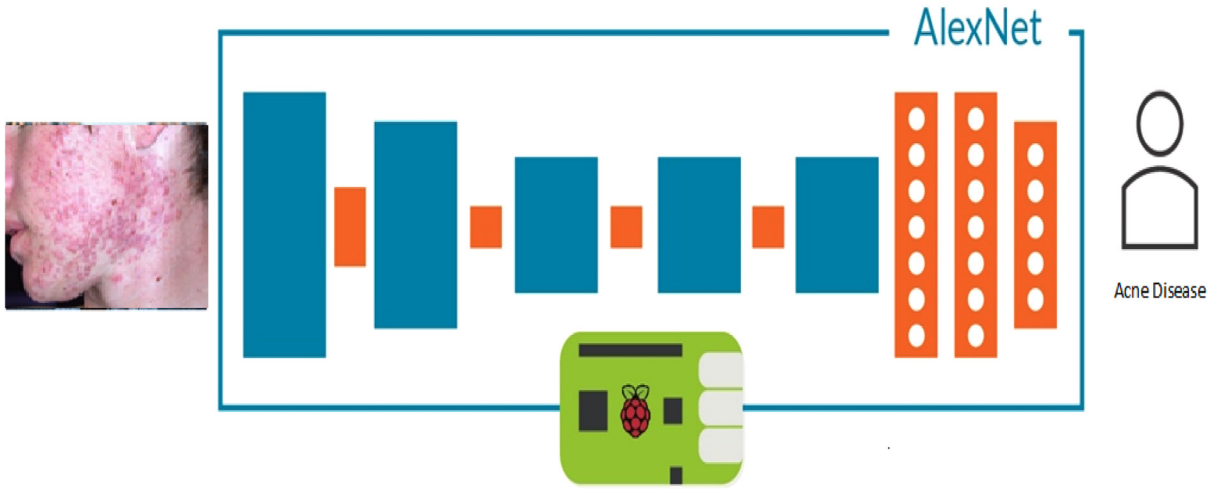

Fig. 9. Skin Disease classification algorithm using Alexnet Architecture

a SoftMax classifier with 4 different class labels. In AlexNET architecture (Fig. 9), Input image size is 227 × 227, first layer is convolution layer, this layer performs convolution operation of input with filter, the filter size is [11 × 11], the output of Convolution Layer 1 is [55 × 55] with 96 features. The second layer is Maximum pooling layer; this layer takes the maximum [3 × 3] value in [55 × 55] image. The output of pooling layer size is [27 × 27] with 96 features. Third layer is convolution layer, this layer performs convolution operation of input with filter, the filter size is [5 × 5], the output of Convolution Layer 2 is [27 × 27] with 256 features. The fourth layer is Maximum pooling layer; this layer takes the maximum [3 × 3] value in [27 × 27] image. The output of pooling layer size is [13 × 13] with 256 feature maps. Sixth layer again convolution layer with the filter size of [3 × 3], and next two layer is again convolution layer so the convolution layer 5 is [13 × 13] with 256 features and this output is fed into maximum pooling layer with kernel of size [3 × 3], the output will be [6 × 6], the output of this layer is fed into fully connected layer 1,2and 3 as shown in Table 2.

Table 2
AlexNET Architecture summary for skin disease detection

Layer	Feature map	Size	Kernel size	Stride	Activation
Input layer	1	227 × 227	-	-	-
Convolution layer 1	96	55 × 55	11 × 11	4	ReLU
Maximum pooling layer	96	27 × 27	3 × 3	2	ReLU
Convolution layer 2	256	27 × 27	5 × 5	1	ReLU
Maximum pooling layer 2	256	13 × 13	3 × 3	2	ReLU
Convolution layer 3	384	13 × 13	3 × 3	1	ReLU
Convolution layer 4	384	13 × 13	3 × 3	1	ReLU
Convolution layer 5	256	13 × 13	3 × 3	1	ReLU
Max pooling	256	6 × 6	3 × 3	2	ReLU
Fully connect layer 1	-	9216	-	-	ReLU
Fully connected layer 2	-	4096	-	-	ReLU
Fully connected layer 3	-	4096	-	-	ReLU
Output layer (FC -4)	-	4	-	-	Softmax

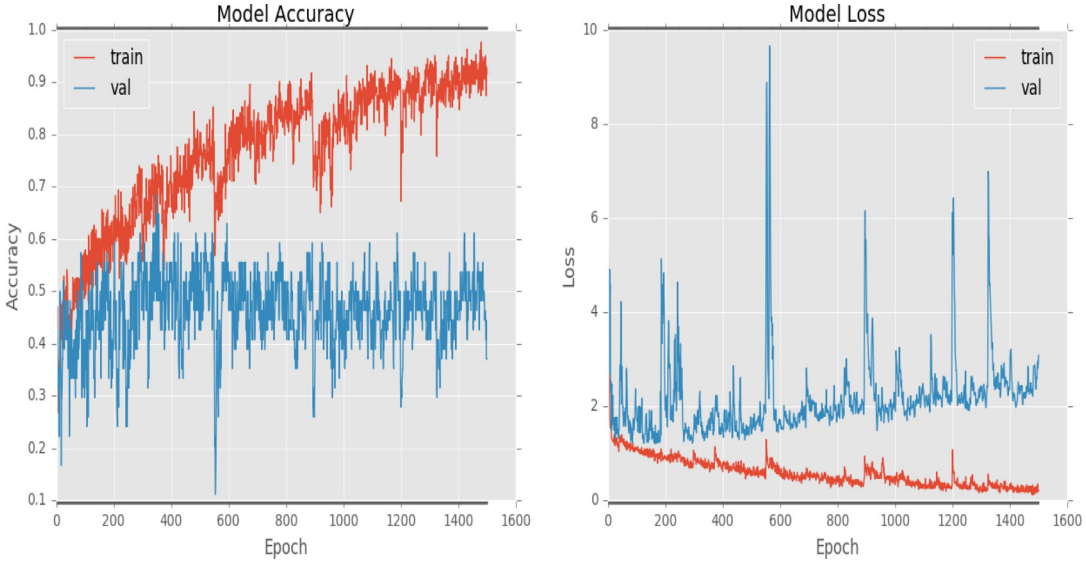

Fig. 10. Indicate the training, validation accuracy and Model loss

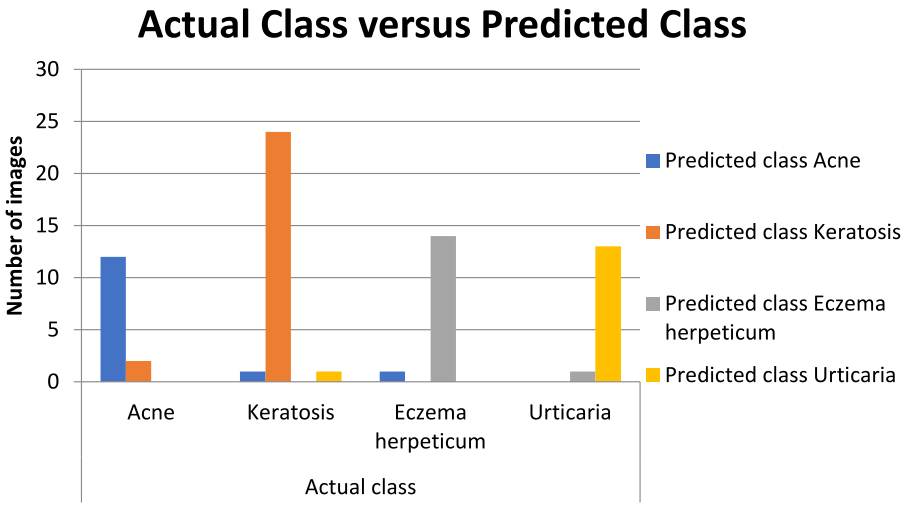

Fig. 11. Actual Class versus predicted class for skin images

The Fig. 10 indicates the training, validation accuracy and Model loss. Our Proposed algorithm achieved 96.32% for training accuracy (dataset) and 62.1% for validation accuracy (10% of training dataset). In case of model loss, initially model loss will be higher, after few iterations, losses are simultaneously decreasing, so finally loss will be saturated between 3 to %. Among the 69 test images, 14 skin disease images are Acne, 26 skin disease images belong to keratosis, 15 skin disease images are Eczema herpeticum and 14 skin disease images are Utricaria. Table 3. shows that 12 images out of 14 are correctly predicted as Acne, 24 images out of 26 are correctly predicted as keratosis, 14 images out of 15 are correctly predicted as Eczema herpeticum, and 13 images out of 14 are cor-

Table 3
Confusion matrix for test images

Classification of skin disease images		Predicted class				Per class accuracy
		Acne	Keratosis	Eczema herpeticum	Urticaria	
Actual class	Acne	12	2	0	0	85.7
	Keratosis	1	24	0	1	92.3
	Eczema herpeticum	1	0	14	0	93.3
	Urticaria	0	0	1	13	92.8

rectly predicted as Utricaria. Fig. 11 displays the bar graph of actual Class versus predicted class for the images of four skin diseases. A learning rate of 0.01 achieved an accuracy of 85.7%, 92.3%, 93.3% and 92.8% for the skin diseases acne, keratosis, Eczema herpeticum and utricaria respectively.

6. Conclusion

A computer vision system for automatic diagnosis of four selected classes of skin diseases is presented in this paper. Images of skin diseases like acne, keratosis, Eczema herpeticum and utricaria obtained from DermNet dataset were considered for testing the performance of the system. One of the key features of the proposed technique is the vast features generated by the convolutional layer of the network which are used by the final layers of the network for classification. Maximum pooling layer is used. A learning rate of 0.01 achieved an accuracy of 85.7%, 92.3%, 93.3% and 92.8% for the skin diseases acne, keratosis, Eczema herpeticum and utricaria respectively. This work can be extended to classify the skin diseases into more number of classes. This work certainly helps the dermatologists to escalate the efficiency of their work and aids them to provide a better treatment for the diseased people. The model presented in this paper can be further enhanced in several ways. First, increasing the data size definitely leads to better result. Second, more ground truth information provided for inter class images will also result in better accuracies.

Declaration of competing interest

The major skin diseases like acne, keratosis, Eczema herpeticum, and Urticaria are taken into consideration and in this paper a deep learning is proposed for automatic grouping of these diseases. The rest of the proposed work is organised as followed. Subdivision II discusses about the recent works in the area of CNN and detection of skin diseases.

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