# Design and Analysis of CNN-Based Skin Disease Detection System with Preliminary Diagnosis

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**Abstract.** Over the past few decades, the occurrence of skin diseases has increased, putting a significant strain on healthcare systems worldwide. These skin diseases can be cancerous (e.g., basal and squamous cell carcinoma, melanoma) and non- cancerous (e.g., acne, vitiligo and eczema). Skin problems can be detrimental to physical health and can cause psychological problems, usually in patients whose face is disfigured or damaged due to skin problems. These dermatologic disorders worsen the situation as time progresses, but the survival rates are high if detected and diagnosed early. This article provides a comprehensive overview of the methods used to classify and detect skin disorders as well as diagnostic methods using naturopathic methods. This paper likewise briefs about the openly available image pre-processing mechanisms and classification algorithms based on the relevant works performed by researchers across the world, and suggests the most suitable technique for each process involved in the skin disease system with appropriate results.

**Keywords:** CNN architecture · Python · Skin disease · Deep learning · Image processing · Naturopathy

## 1 Introduction

Skin is said to be the most sensitive and the largest part of the human body. Skin disorders are one of the most widespread health issues which create an impact on the appearance of the skin. The primary sources of skin diseases are fungi, allergies, bacteria and viruses. At a later stage, this may be the reason for chronic infections, which affect victims for a longer period of time. In many cases, especially in rural and tribal areas, people tend to ignore skin lesions by comparing them to common infections. Still, a lack of proper diagnosis can cause severe inflammation and worsen the situation. Most of these diseases may take lots of time to show symptoms and are difficult to detect. Sometimes the tests recommended by hospitals to diagnose the disease may be the reason for other harmful effects on the human skin. In order to eliminate these costs and the harmfulness of the examination to the human body, we propose an automatic classification system for skin diseases. Such an automated diagnosis system can be realized using the aid of artificial intelligence and convolutional neural networks (CNN).


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Convolutional neural networks help extract useful features from images, eliminating the need for traditional manual image processing techniques. CNNs effectively reduce the number of defining properties without losing the quality of designed models. Due to these advantages, CNNs are said to have better efficiency in classifying images based on the given dataset. Python is at present the most accepted, mature, and widely adopted programming language for machine learning. In addition to this, Computer Vision allows the computer to determine the feature of different objects using digital images or videos. Implementing CV in Python is useful for developers when programming tasks related to visual concepts, separations, and other image processing steps.

There has been over the past few years an upward trend in the usage of harmonizing and substituting medicines because of the disadvantages related to the traditional chemotherapic treatments and the possible advantages of using better natural options. Phytochemical compounds derived from the extracts of different parts of plants like leaves, barks and roots have shown capability and potential to function as anticancer drugs, or for acting as base compounds in synthesizing new naturopathic drugs.

## 2 Literature Survey

Various research papers have been proposed that deal with the classification and precise information about different skin diseases. For instance, Vinay Gautam et al. [1] proposed a high-performance CNN to detect and classify skin diseases at an earlier stage, while Dan Popescu et al. [3] presented a methodical overview of recent developments in the field of increased interest in skin disease prediction.

To address the overfitting and deprivation issues in the network, Viswanatha Reddy Allugunti [2] proposed using residual learning algorithm, while Md. Al Mamun and Mohammad Shorif Uddin [4] evaluated the methods and techniques used to diagnose 21 commonly observed skin diseases and related them to available image databases. Kritika Sujay Rao, Pooja Sureh Yelkar and Omkar Narayan [5] presented a layered deep-learning model to differentiate healthy vs diseased skin lesion using CNN algorithm.

Several research papers have also proposed datasets of skin diseases that are used in Computer-Aided Diagnostic (CAD) systems worldwide. Bing Xie et al. [15] proposed a skin disease dataset dominated by Asian species with the bounding box label named XiangyaDerm. It contains over 107,000 medical images covering more than 500 types of skin disorders, while Zhe Wu et al. [16] studied various CNN algorithms for classifying facial skin lesions based on dermoscopic images and identified six common skin diseases. Rowin Veneman [10] developed a smartphone application which can detect current skin lesions using segmentation and detection of objects, while S. Chatterjee, Debangshu Dey & Sugata Munshi [11] reported a procedure for the advancement of four class skin disease identification technique. I Gunadi et al. [13] also presented the real-time execution of an application using Open CV library supported with Python in medical image processing.

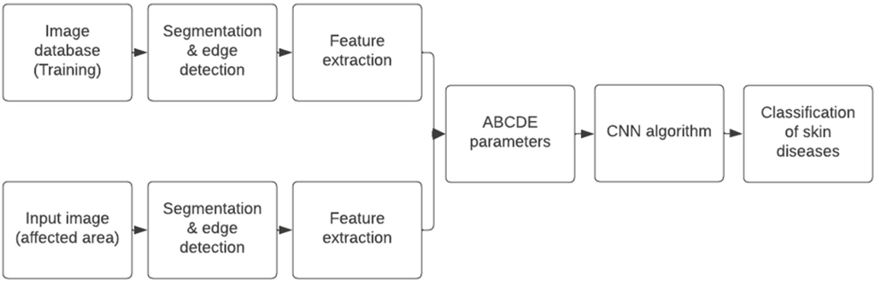


**Fig. 1.** Workflow representation of proposed model

## 3 Design and Analysis

### 3.1 Design Workflow

The procedural flow of the proposed model (Fig. 1) is based on two processes – the first includes data acquisition from an appropriate image database, followed by segmentation and contour (edge) detection to obtain the features of the skin lesion from training dataset, which serve the purpose of training the CNN model, while the second process involves data acquisition from the captured input image to compare with the existing model pre-trained with the skin disease dataset. The features of given input image are compared with those of the possible disease affected images present in the system through CNN algorithm in order to classify the type and intensity of the skin disease present in the input image [3].

### 3.2 Image Acquisition

Every machine learning model is designed using two sets of data – the training dataset and the test dataset, which might be in the form of texts, images, audio or numerical types. There are different types of datasets available in open source for the purpose of skin disease classification. Some of these are DermNet, ISIC, HAM10000 etc. HAM10000 is a set of clinical images and infected tissues acquired from different populations and saved using different modes and methods. The dataset consists of over 10,000 images that shall be implemented as the training database for academic machine learning purposes [7].

Out of the available options, HAM10000 is preferred due to large diversity in datasets (Fig. 2) and properly classified images to train the machine learning model. This study involves the analysis of seven types of skin diseases, namely melanocytic nevi (nv), melanoma (mel), benign keratosis lesions (bkl), actinic keratosis & intraepithelial carcinoma (akiec), vascular lesions (vasc), dermatofibroma (df) and basal cell carcinoma (bcc). The dataset includes numerous images pertaining to each disease, supported by metadata which consists of the gender and age of the person along with the location of disease. These images are forwarded to the image processing setup, while the related information is forwarded to the machine learning model.

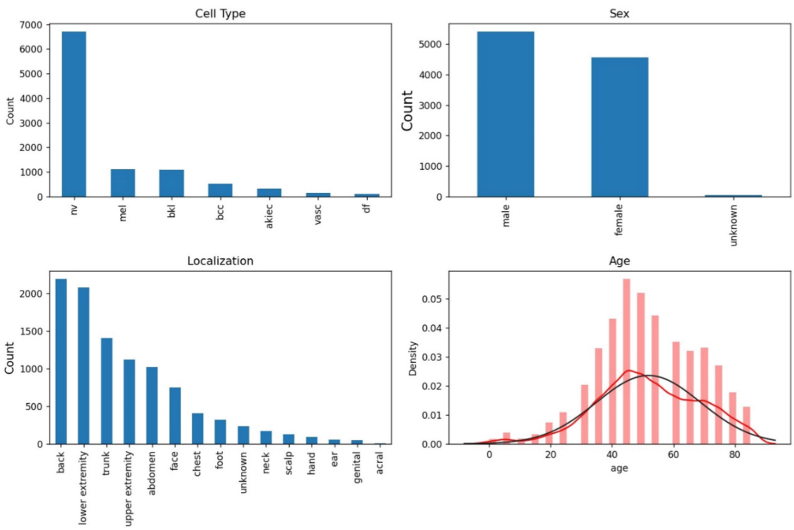


**Fig. 2.** Graphical analysis of HAM10000 dataset

### 3.3 Image Pre-Processing

The image processing stage begins with image preprocessing, which is necessary for eliminating the unwanted and redundant details from skin images such as noises and hairs. For this, there are various morphological filters such as minimum, maximum, Gaussian and median filters that use special operations and transform a given image. In these preprocessing filters, each pixel is modified based on comparison with neighboring pixels in the task window. The maximum filter is a pre-processing technique which replaces each pixel by the darkest (maximum) pixel of the neighboring elements, while the minimum filter, similarly, replaces the pixels with the lightest (minimum) pixel of the neighboring elements. The Gaussian filter is a smoothing filter that performs 2-D convolution for removing noises and irrelevant details from the input image. The functionality is somewhat similar to a mean filter, but the filter uses a unique aggregation function that represents the shape of a Gaussian, i.e., bell-shaped hump (Fig. 3).

Given an input image of size M x N, and a filter window of size W x W, where W is an odd number, the output image O(i,j) at pixel (i,j) is given by:

$$O(i, j) = median(I(i + k, j + l)) \tag{1}$$

$$fork, lin[-W/2, W/2]$$

where I is the input image, and median is the function that returns the median value of a set of values. In other words, for each pixel in the image, the median filter takes the values of all the pixels in the surrounding window and computes the median value. This value is then assigned to the central pixel in the output image.

| Input | | | | | |
|---|---|---|---|---|---|
| 1 | 4 | 0 | 1 | 3 | 1 |
| 2 | 2 | 4 | 2 | 2 | 3 |
| 1 | 0 | 1 | 0 | 1 | 0 |
| 1 | 2 | 1 | 0 | 2 | 2 |
| 2 | 5 | 3 | 1 | 2 | 5 |
| 1 | 1 | 4 | 2 | 3 | 0 |

| Output | | | | | |
|---|---|---|---|---|---|
| 1 | 4 | 0 | 1 | 3 | 1 |
| 2 | 1 | 1 | 1 | 1 | 3 |
| 1 | 1 | 1 | 1 | 2 | 0 |
| 1 | 1 | 1 | 1 | 1 | 2 |
| 2 | 2 | 2 | 2 | 2 | 5 |
| 1 | 1 | 4 | 2 | 3 | 0 |

Sorted:
0,0,1,1,**1**,2,2,4,4

**Fig. 3.** Median filtering (3x3 window)

### 3.4 Image Segmentation

The pre-processed image is subjected to various segmentation processes where the specific area of infection is detected from the entire image by grouping similar regions under their respective class labels. Under image segmentation, various techniques based on threshold limiting, region wise classification, edge/contour detection and sample clustering are implemented.

Threshold-based segmentation is a method where an image is segmented into two or more regions based on a specific threshold value. The threshold value is set to a specific level, and pixels with intensities above or below this value are classified into different regions. Region-based segmentation groups pixels with similar characteristics into segments or regions based on some predefined criteria. This method involves partitioning the image into homogeneous regions, where pixels within the same region have similar color or texture features. Edge-based segmentation involves detecting edges in an image and then partitioning the image into regions based on these edges. This method is based on finding discontinuities in the image, such as changes in brightness or texture, to separate the image into regions.

Clustering algorithms are able to provide reasonably accurate segments within a small amount of time. Mainstream algorithms like the K-means clustering algorithms [19] are unsupervised algorithms that work by grouping pixels with mutual attributes together as belonging to a particular segment. In K-means clustering (Fig. 4), the central locations of each cluster are generally located at different positions, followed by every point of data being plotted to the nearest centroid. These are then shifted to the mathematical average position of data points which are accordingly plotted, as illustrated by (2), (3) and (4).

The primary function is denoted by F, where $n_{ik}$ equals 1 if $x^i$ belongs to cluster k, or else $n_{ik}$ equals 0. In this equation, $\mu_k$ represents the position of centroid of the corresponding cluster.

$$F = \sum\nolimits_{i=1}^{m} \sum\nolimits_{k=1}^{K} n_{ik} \|x^i - \mu_k\|^2 \tag{2}$$

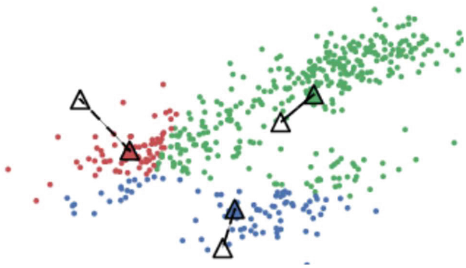

**Fig. 4.** K-means clustering using three centroids

This function is minimized first with respect to $n_{ik}$ by treating $\mu_{ik}$ as a constant term in order to update the assignments of each cluster.

$$\frac{\partial f}{\partial n_{ik}} = \sum\nolimits_{i=1}^{m} \sum\nolimits_{k=1}^{K} \|x^i - \mu_k\|^2 \tag{3}$$

Later the objective function F is minimized with respect to $\mu_k$ in order to reconfigure in order to compute and calculate the centroid of each cluster with improved accuracy. Equation 3 represents the final equation for calculating the centroid of the corresponding cluster k.

$$\frac{\partial f}{\partial \mu_k} = 2\sum_{i=1}^{m} n_{ik}(x^i - \mu_k) = 0$$

$$\Rightarrow \mu_k = \frac{\sum_{i=1}^{m} n_{i_k} x^i}{\sum_{i=1}^{m} n_{i_k}} \tag{4}$$

### 3.5 Feature Extraction

After capturing the infection site, characteristic signs of skin lesions are extracted by numerical counting of symptoms. Some of the popular feature extraction algorithms include local binary pattern, gray level co-occurrence matrix, wavelet and discrete cosine transforms and ABCD diagnosis [3].

The Local Binary Pattern (LBP) is a texture descriptor that extracts information by comparing each pixel with its neighbouring pixels, making it invariant to changes in illumination and relatively robust to small variations in texture patterns. Gray Level Co-occurrence Matrix (GLCM) is a statistical method that analyses the distribution of pixel value pairs in an image by calculating the co-occurrence of pixel intensity values at a specific distance and direction. Wavelet Transform is another mathematical technique that analyses signals and images at multiple scales by computing the inner product of the signal with a set of wavelets characterized by their frequency and location.

The ABCD parameters (Fig. 5) are a set of clinical features used to easily evaluate skin lesions and to identify potential skin cancer. When considering melanomaic skin lesions, dermatologists use the ABCD rule to detect melanoma early [18]. ABCD stands for Asymmetry, Borders, Colour and Diameter.

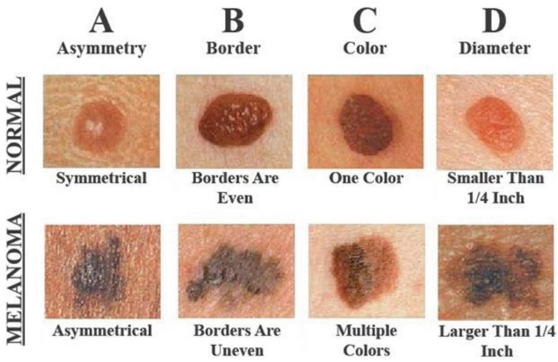


**Fig. 5.** ABCD parameters for skin cancer

1. Asymmetry (A) - one half of the skin lesion must be different from the other half

$$Symmetry = (Area\ of\ \ left\ side)/(Area\ of\ \ right\ side) \tag{5}$$

2. Borders (B) - the skin lesion would be having irregular and poorly defined borders.

$$Border\ irregularity = Perimeter\ of\ \ mole/Length\ of\ \ longest\ axis \tag{6}$$

3. Colour (C) - the colour of skin lesion may vary from darker shades such as brown, black or tan. In rare cases, this might be white, red or blue in colour. There is no specific equation for colour variation, but it can be identified through visual inspection in terms of hex-coding of RGB values from 0–255.

4. Diameter (D) - the longest distance between the borders of the skin lesion would be a minimum of 6mm in length.

$$Diameter = 2\ x\ (Square\ root\ of\ \ (Area\ /\ pi)) \tag{7}$$

The overall ABCD score is calculated to determine whether the given image is cancerous or non-cancerous.

$$Score = [(A * 1.3 + B * 0.1 + C * 0.5 + D * 0.5)] \tag{8}$$

Based on these parameters and overall score defined by (5) to (8), the values are forwarded to the neural network algorithm used for detecting the particular skin disease. The greater the resemblance of these criteria with the examined image segment, greater the chance of this examined image segment to be a skin cancer. Such features can be extracted from the input images which are represented by numerical coefficients. These numbers act as input data to the machine learning model.

### 3.6 Machine Learning Stage

This stage involves the usage of deep learning algorithms and CNN models in order to detect the disease present in the infected area of the given image. CNNs are mostly analogous to other neural networks, but they contain an additional stage of processing due to the fact that they are comprised of a sequence of convolutional layers. The below figure (Fig. 6) represents the schematic view of a basic CNN architecture. Some of the common CNN architectures include Inception, Xception, VGG Family, ResNet-50 etc.

Inception architecture makes the neural network wider by connecting multiple layers in parallel with different filters and adding them to move to the next layer. Xception improvises on older architectures by implementing depth-separable convolution operations. The VGG Family is, above all, a simple and easy-to-understand CNN architecture. In the VGG architecture, convolutional layers are added to the aggregation filter size. VGG-16 and VGG-19 are more widely used.

The ResNet-50 architecture consists of 50 layers that are stacked to form a deep neural network. It uses link connections, also called residual connections, to allow the network to learn more efficiently and avoid the problem of leakage gradients. The network is trained using backpropagation with stochastic gradient descent, where the weights of the network are adjusted to minimize the difference between the predicted output and the actual output. Once trained, the ResNet-50 model can be used for image classification tasks, where it takes an input image and predicts the probability that the image belongs to a certain class. The model has been shown to achieve high accuracy on a variety of image classification benchmarks (Fig. 7).

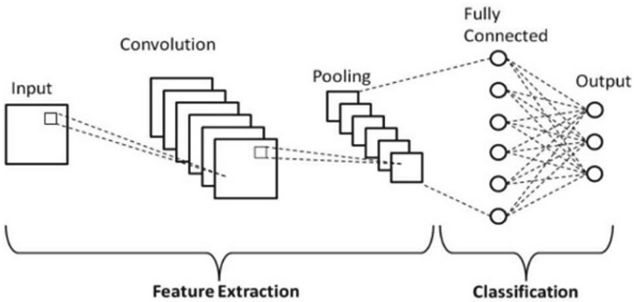


**Fig. 6.** Schematic view of CNN architecture

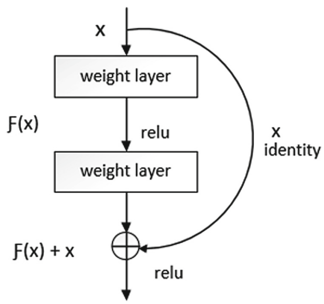


**Fig. 7.** ResNet-50 functional design

A residual block consists of two convolutional layers followed by an element-wise addition of the input to the output of the second convolutional layer. This creates a shortcut connection that allows the gradient to flow directly through the block without passing through additional layers. Hence, we can infer from the above figure that an identity connection is created which results in the consequent layers to learn the residue F(x). This helps in reuse of appropriate functions of activation from the previous layers without the addition of further complexities [9].

### 3.7 Preliminary Diagnosis

There are three types of harmful skin cancer: basal cell carcinoma (BCC), squamous cell carcinoma (SCC) and melanoma. The cutaneous lesions of BCC form flat, solid, yellow scar-like areas with raised edges and contain uncharacteristic blood vessels that dilate like conventional spokes of wheels. In squamous cell carcinoma, the infected area is found as a hard red patch that is rough, bloody, and can grow like a wart. Melanoma often looks like a black or brown spot, but can also be peach and pink, like human skin color [17]. A variety of naturopathic medications are readily available for the treatment of skin disorders that present good results, especially if these disorders are identified and accordingly treated in the premature stages of development itself. Some of the commonly used oils that can be applied epidermally include olive oil, sunflower oil, sesame oil, pomegranate seed oil etc., while certain phytochemicals which are found in grapes (resveratrol), soybeans (genistein) and eggplant (SRGs) also exhibit significant properties in the treatment of skin cancers [17]. Such remedies would be provided by the skin disease detection system with appropriate quantities which acts as primary medication and help in preventing the spread of infection into the internal organs of the infected person.

## 4 Results

In this study, image segmentation methods are applied and compared using images of skin diseases and a sample set of 25 images were used to compare these algorithms based on three factors – sensitivity, specificity and accuracy [8, 21]. Mathematical descriptions of these terms are given in (9), (10) and (11). TP and TN represent images representing “true positives” and “true negatives,” while FP and FN represent false positives and false negatives, the four parameters used to calculate the above ratios. Table 1 shows a comparison of image segmentation methods.

$$Sensitivity = TP/(TP + FN) \tag{9}$$

$$Specificity = TN/(TN + FP) \tag{10}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

The behavior of every deep learning model can be represented by a specific parameter known as the ‘confusion matrix’. It is defined as a tool used to analyze the effective

**Table 1.** Comparison of segmentation methods

| **Method name** | **Performance metrics** | | |
|---|---|---|---|
| | ***Sensitivity(%)*** | ***Specificity(%)*** | ***Accuracy(%)*** |
| Thresholding-based (Otsu) | 77.69 | 71.42 | 71.22 |
| Region-based (Region split and merge) | 65.47 | 74.17 | 69.81 |
| Edge-based (Gradient) | 73.65 | 71.13 | 77.10 |
| Clustering-based (K-Means) | 76.17 | 89.55 | 83.31 |

behavior of a classification model by showing the number of true and false predictions made by the model. The matrix is usually presented in the form of a table, where the columns depict the class predicted by the model while the rows represent the original class. The proposed model has seven types of classification of diseases, which results in a confusion matrix with an order of 7 (seven rows and columns), labelling each disease from 0 to 6. It can be inferred from the above matrix that when the predicted label matches the true label, the highest score is obtained in each row, indicating the overall accuracy of the model as a cumulative average of the scores present across the diagonal of the matrix. The performance of a neural network can also be analyzed using model accuracy and model loss with respect to increase in number of epochs (groups of images). The overall accuracy of the model is found to be close to 97%, whereas the loss of data from images is minimized to 7% (Fig. 8).

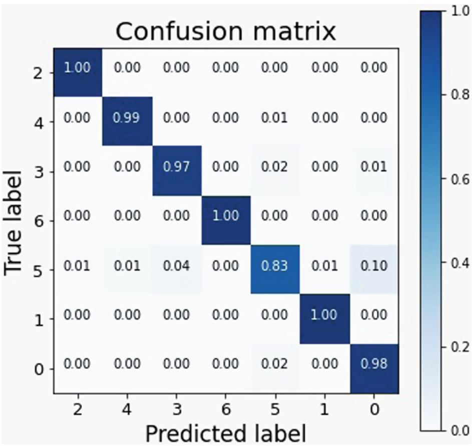


**Fig. 8.** Confusion matrix of proposed model

## 5 Conclusion

The design of an automated skin disease system is composed of image processing as well as machine learning stages, which are supported by different types of mechanisms. The image acquisition process is executed using the HAM10000 dataset [7] which provides a clear overview of the types of skin diseases present across the globe.

The image processing stage consists of data cleaning or image pre-processing which is done using median filters [20], followed by image segmentation process implemented using K-means clustering mechanism [19], and the features are extracted following ABCD rule for skin cancer detection [18] using the overall score used for classifying the lesion as cancerous or non-cancerous. When it comes to the design of a trained machine learning model, we make use of deep CNN algorithms [16] in order to classify the type of skin disease present in the input images through automated visual inspection. From the comparisons drawn between different CNN methodologies, ResNet-50 is the most suitable architectures for implementing CNN modelling in the diagnosis of skin-related disorders. Since the diagnosis of each and every disease might not be feasible within the scope of this paper, this work could be extended towards providing more efficient natural remedies for a wider range of diseases.

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