# Deep Learning Approach for Performance Evaluation of Pre-trained Network in Predicting Skin Disease

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**Abstract**

The Prediction of skin diseases becoming challenging task even for dermatologist working from many years because of too tiny contrast between surrounding skin and lesions, the usual resemblance between skin lesions. In order to diagnose and treat skin diseases, doctors currently use a biopsy procedure that is examined and carried out by them. A hybrid approach can avoid human judgment, producing positive results quickly. A thorough examination suggests that frameworks for recognizing various skin disorders may be built using deep learning techniques. To find skin illnesses, it is necessary to distinguish between skin and non-skin tissue. Computer-aided vision system helps eliminate to prognosis malignant skin lesions at the earliest time. With the advent in the deep learning includes CNN to have improved accuracy in prediction. To evaluate the performance and implement CNN for identifying skin disease, we have chosen the transfer learning with the popular architectures like Resnet50, Resnet101, AlexNet and Squeezenet.

*Keywords*: Deep Learning, Skin Disease, Performance, F1 Score, Accuracy, Precision, SVM, classifier, Feature extraction, Recall, Pre-trained network, Resnet-50, Resnet-101, Alexnet, Squeezenet.

## 1. Introduction

One of the most prevalent illnesses in the world is skin disease. Skin conditions come in many different forms, including squamous cell carcinoma (SCC), intraepithelial carcinoma, melanoma, and basal cell carcinoma (BCC) [1]. Research has shown that skin cancer, in particular, is the most prevalent cancer in the United States and that one-fifth of all Americans will develop skin cancer at some point in their lifetime [2, 3]. With a death rate of 1.62% among all skin cancers, melanoma is said to be the most lethal type [4].

The American Cancer Society predicts that there will be roughly 100,350 new instances of melanoma in the country in 2020 and that 6,850 individuals will pass away from the disease [5]. Contrarily, BCC is the most prevalent form of skin cancer, and although while it seldom results in death, it has a significant negative impact on healthcare services [6]. Thankfully, early skin cancer detection and treatment can increase five-year survival rates by about 14% [7].

However, correctly identifying a skin illness is difficult since it requires a number of visual cues, including the individual lesion morphology, the body site distribution, color, scaling, and arrangement of lesions. The diagnosing procedure can be difficult to understand when the different components are examined independently [8].

For melanoma, the ABCD rules, pattern analysis, Menzies method, and 7-Point Checklist are the four main clinical diagnosis techniques. Only doctors with plenty of experience can frequently use these techniques to make accurate diagnoses [9].

The gold standard for determining the existence of a skin illness is the histo-pathological analysis of a biopsy taken from a suspicious lesion. Numerous illustrations of various skin conditions are shown in Fig. 1. So, it would be advantageous to develop a technology that can automatically distinguish between skin cancer and non-cancer and differentiate between different types of skin cancer.

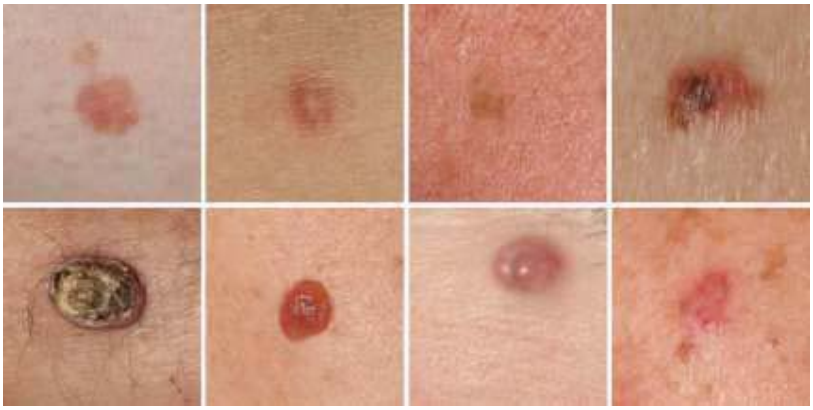


Fig. 1. Numerous illustrations of various skin conditions. The Dermofit Picture Library is where these pictures were found [10].

In this world of development, knowledge, progress, the advancements in research have reached such a high stage, where it won't be wrong to say that this is the "Computer World". Wherein, almost all processes are being taken up by the computer programs. So is the field of Artificial Intelligence being raised to an extent where diagnosing the disease at the initial stage won't require visiting a doctor. We can get to know about the disease by just placing their symptoms in the Expert System.
In this article, we tried to evaluate the performance of pre-trained networks using deep learning in predicting skin disease. Deep Learning sounds quite similar to Machine Learning. No doubt, both contribute to Artificial Intelligence as a whole, deep learning and machine learning do have differences.

## 2. Skin Disease

The human body's largest and thickest organ, the skin is made up of the epidermis, dermis, and hypodermis. The three primary functions of the skin are protection, sensation, and thermoregulation, and they all work together to offer a strong defense against environmental assault. The epidermis' top layer, the stratum corneum, is a layer of protective tissue that is optically neutral and varies in thickness. Keratinocytes in the stratum corneum create keratin, which is beneficial to the skin's ability to shield the body. The stratum corneum scatters light when it strikes the skin. Melanocytes are present in the epidermis' basal layer. In particular, melanocytes cause the skin to produce melanin, a pigment that gives skin its tan or brown hue. By producing more melanin, melanocytes serve as filters and shield the skin from damaging ultraviolet (UV) rays from the sun. The number of melanocytes determines how much UV radiation is absorbed. Melanoma, however, is brought on by melanocytes that develop abnormally. The middle layer of skin, known as the dermis, is made up of collagen fibers, sensors, receptors, blood vessels, and nerve endings. It gives the skin flexibility and vitality [32]. Nucleotide molecules make up Deoxyribonucleic Acid (DNA), which is made up of them. A phosphate, sugar, and nitrogen base are all components of a nucleotide. The genes are created from the sequence of nitrogen bases in the DNA. Cell development, division, multiplication, and death are all controlled by genes. Cell division and proliferation are regulated by oncogenes. Tumor suppressor genes are often referred to as protective genes. They typically do this by keeping track of how quickly cells divide into immature cells, repairing damaged DNA, and regulating when a cell dies. When the tumor suppressor genes mutate, a cell becomes uncontrollable and eventually forms a mass known as a tumor (cancer). The DNA can be harmed by UV radiation, which leads the melanocytes to manufacture melanin at an excessively high rate. A healthy quantity of UV radiation helps the skin produce vitamin D, but too much can lead to pigmented skin lesions [34]. Melanoma is the name given to the malignant tumor that develops when melanocytes proliferate abnormally [35]. Malignant melanoma (MM), squamous cell carcinoma, and basal cell carcinoma are the three main subtypes of skin cancer. The latter two, termed as keratinocyte carcinoma, in particular, are derived from basal and squamous keratinocytes (KC). In the United States, about 4.3 million cases of BCC and 1 million cases of SCC are identified each year, though it's probable that these figures are understated [36]. These are the most frequent skin malignancies that affect both men and women. Nevertheless, MM, an aggressive melanocyte malignancy is a less prevalent but significantly more lethal form of skin cancer. It frequently begins tiny and gradually grows and changes in color. Melanin's hue primarily depends on where it is located in the skin. Melanin found in the stratum corneum is what gives skin the color ebony. The top epidermis, papillary dermis, and reticular dermis are each shown to be light to dark brown, gray to gray-blue, and steel-blue, respectively. The excessive melanin deposit is present in the epidermis in cases of benign lesions. The most significant indication of melanoma that causes noticeable vicissitude in skin color is melanin present in the dermis. In addition to pale lesion regions with a significant blood supply at the periphery, thicker collagen fibers are one more indicator of melanoma. The pigmented lesion's shape, size, color, border, and symmetry are further gross morphologic characteristics. If the ocular approximation confirms a suspicion of skin cancer, a biopsy and histology are necessary to provide an exact diagnosis [37]. There are four main kinds of melanoma based on microscopic evaluations of the lesion: superficial

spreading melanoma (SSM), nodular melanoma (NM), lentigo malignant melanoma (LMM), and acral lentiginous melanoma (ALM).

## 3. Skin disease diagnosis with deep learning

As deep learning has grown in popularity, it has been applied to a variety of dermatological problems. Here, we take a look at the research that has already been done using deep learning to diagnose skin diseases. From a machine learning viewpoint, we first offer a general overview of the data preparation and augmentation techniques used in deep learning, and then we present a literature evaluation of deep learning's applications in skin disease detection organized by task type.

### *3.1. Data preprocessing and augmentation*

#### *3.1.1. Data preprocessing*

When using deep learning to diagnose skin diseases, data preparation is crucial. Since skin disease datasets (like ISIC, PH2, and AtlasDerm) contain images with widely varying resolutions, and deep networks typically accept inputs with certain square sizes (like 224 by 224 and 512 by 512), it is necessary to crop or resize these images before feeding them into deep learning networks. Images may be distorted or lose important details if they are resized or cropped directly to meet specific dimensions [13, 32]. Practical solutions to this problem include scaling images uniformly along their shortest side while preserving their aspect ratio. Before being fed into a deep learning network, images are usually normalized by subtracting the mean value and dividing by the standard deviation, both of which are calculated over the whole training subset. Since the lighting, skin tones, and perspectives of skin disease photos can vary widely across a dataset, it has been observed in previous publications [33, 32] that subtracting a uniform mean value does not properly normalize the illumination of individual photographs. Yu et al. [32] corrected this by removing the image's channel-wise mean intensity values from each individual image to normalize them. The experimental results presented in their research demonstrated that the performance of a deep network degrades when the mean pixel value is subtracted. Moreover, hair or other unrelated stuffs should be deleted from skin pictures using techniques such thresholding methods [34, 35], morphological approaches [36], and deep learning algorithms [22, 21, 22] for more accurate segmentation and classification.

#### *3.1.2. Data augmentation*

It is well-known that training a deep learning network requires a vast amount of data in order to prevent overfitting and produce optimal results. Unfortunately, large amounts of labeled training data are difficult to come by for many applications, such as skin disease diagnosis. Due to factors such as disease rarity, patient privacy, the need for labeling by medical specialists, and the high expense to gather medical data, medical image analysis typically works with limited data [37]. To address this challenge, researchers have devised techniques for "data augmentation," which involve artificially modifying the original data using the right techniques to enhance the quantity of accessible training data. It is possible to increase the quantity and quality of the available training data through the use of feasible data augmentation techniques. Deep learning systems can pick up more useful features like rotation and translation invariance with more training data. Geometric transformations (such as flipping, cropping, translating, and rotating), color space augmentations, kernel filters, mixing images, random erasing, feature space augmentations, adversarial training, generative adversarial networks, neural style transfer, and meta-learning are all common data augmentation techniques [37]. The 4,000 dermoscopy images used by Al-Masni et al. [38] were rotated by 0, 90, 180, and 270 degrees to provide additional training data. By doing so, we were able to lessen the effects of over-fitting and increase the deep networks' stability. The photos were rotated by 0, 90, and 180 degrees by Yu et al. [32], and then randomly translated (with a shift between -10 and -10) pixels. Experiments conducted on the ISIC skin dataset showed a considerable improvement after data augmentation was used. For a more in-depth discussion of data augmentation, the reader is directed to the work of Shorten et al. [37].

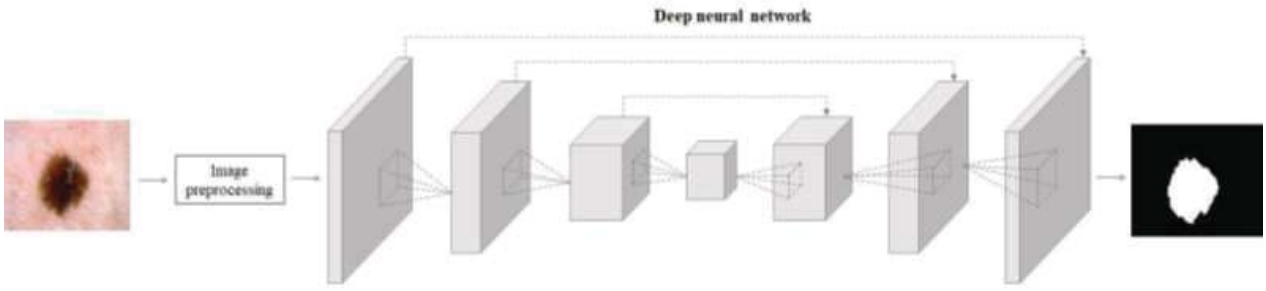



Fig. 2. The workflow of a typical skin disease segmentation task

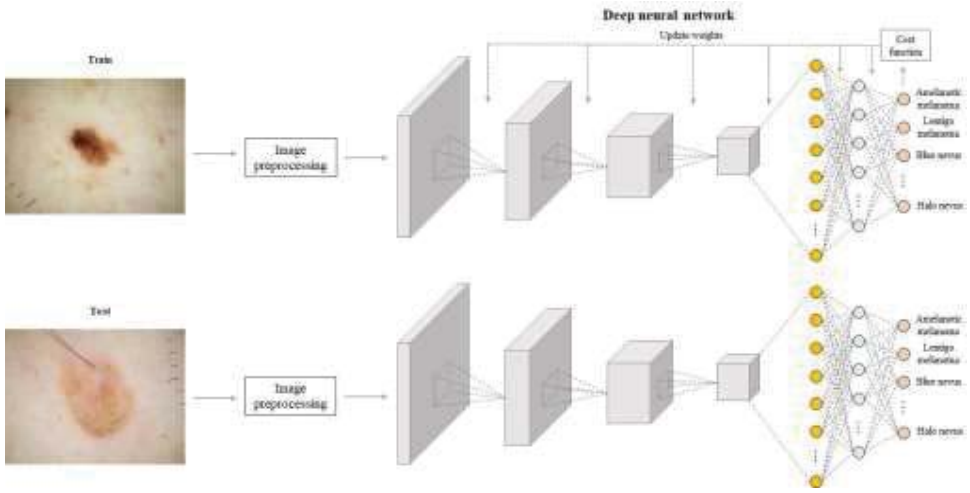



Fig. 3. The workflow for a typical skin disease classification task

## 4. Methodology:

### *4.1. Dataset:*

The DermNet Skin Disease Atlas collected and labeled over 23,000 photos and made them accessible for free use as the DermNet dataset. The URLs for the remaining photographs looked to be broken, so limited images were downloadable. Nevertheless, the data had a few redundant sub-classes that were either blank or otherwise unimportant. From http://www.dermnet.com/dermatology-pictures-skin-disease-pictures, we gathered data consisting of images of 08 different skin illnesses. The table below shows type of skin illnesses and the number of samples of each type collected for our experiment.

Table 1. Type of Skin Illnesses and Data Collected

| Skin Illness Type | Number of Samples Gathered |
|---|---|
| Acne | 355 |
| Actinic Keratosis | 214 |
| Basal Cell Carcinoma | 444 |
| Hives | 121 |
| Nail Infection | 148 |
| Psorasis | 691 |
| Rhus Dermatitis | 115 |
| Rosacea | 196 |

There are altogether 2,284 samples in total, with a proportion of 80 % used for training and the rest 20% images used for testing. Images are in JPEG format, which uses three channels (RGB) to represent color. While there is some variation in image and category resolutions, none of this is really high-resolution data.
The block diagram in figure 4 shows the step by step process of predicting skin disease with Deep learning models

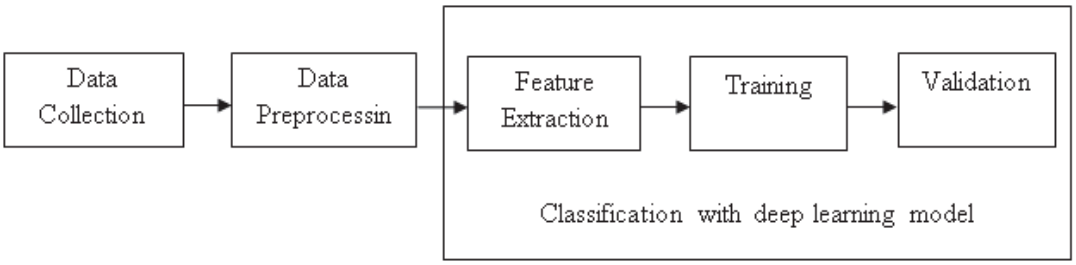



Fig. 4. Proposed model using deep learning algorithm

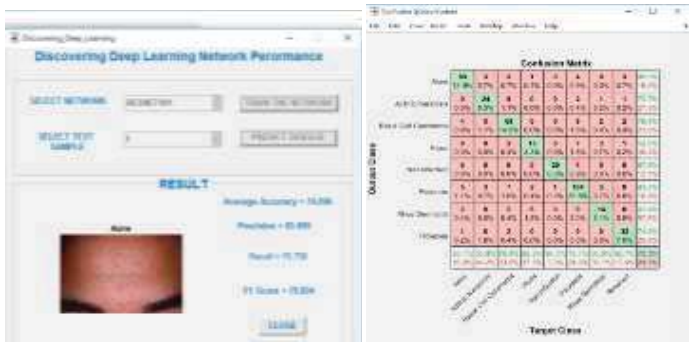
## 5. Results

The Pre-trained learning models namely ResNet50, ResNet101, AlexNet, SqueezeNet are considered here in this experiments. In order to evaluate the performance of Pre-trained model with deep learning approach, we calculated four different metrics viz accuracy, precision, recall, F1 score.

The most popular option for resolving challenging computer vision issues has been deep learning methods. Model correctness is the most common evaluation statistic used to determine an algorithm's performance. For a very long time, the primary parameter utilized to compare machine learning models was accuracy.

- How often a model correctly predicted throughout the entire dataset is determined by the accuracy statistic. This measure can only be trusted if the dataset is class-balanced, meaning that each class contains an equal amount of samples.
- How many of the model's "positive" predictions came true is a measure of precision.
- Recall: Recall measures how many of the positive class samples present in the dataset were correctly identified by the model.
- Accuracy, on the other hand, merely measures the proportion of times a model correctly predicted across the full dataset, which is still valid if the dataset is class-balanced.
- An alternative machine learning evaluation statistic called F1 score evaluates a model's predictive ability by focusing on its performance inside each class rather than its overall performance as is done by accuracy. A model's precision and recall scores are combined into one metric, the F1 score, which has led to its extensive use in recent research.

We used precision and recall as a criterion to assess the performance of these pre-trained models because our dataset is very unbalanced and of the multiclass type. Figure 5 (a) through (j) shows the results from the proposed system.




(a) (b)

(c) (d)


(e) (f)

(g) (h)

(i) (j)

Fig. 5. Screenshots and Confusion Matrix of the proposed system implemented in MATLAB

## 6. Conclusion

In the near future, initial disease diagnosis won't require a trip to the doctor thanks to advancements in artificial intelligence. By just entering the disease's symptoms into the Expert System, we can learn more about the condition. Deep learning has becoming more popular since it requires less data samples while still producing amazing results. This article illustrates how well deep learning-based pre-trained networks do at predicting skin diseases.

Thus, we may draw the conclusion that ResNet50 has demonstrated the most promising results in identifying 8 distinct skin diseases, needing less training samples and no transfer learning. After transfer learning, AlexNet and SqueezeNet may become more effective in our instance.

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**Acknowledgement**

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