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# Robust Skin Disease Diagnosis with Deep Belief Network

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***Abstract.*** *The skin is one of the first lines of defence against environmental influences such as sunlight, bacteria and germs, which cause various skin diseases. In addition to the bad psychological and physical impact caused by skin disease. So, in recent years, many artificial intelligence (AI) algorithms have appeared that can recognize Images, through which skin diseases can be diagnosed, avoiding traditional methods that rely on visual examination and self-evaluation based on experience. The paper aims to classify a group of skin diseases according to the type of disease, such as Atopic Dermatitis, Dyshidrotic Eczema and Nummular Dermatitis using a deep belief network algorithm (DBN) that was built to suit the work. A global dataset was also used, obtained from the Kaggle website, and after conducting experiments on it, the algorithm achieved high accuracy in diagnosing diseases, the percentage reached 98.773%. It is possible in the future to use the network to classify other types of diseases after providing it with a large number of images of affected people.*

***Keywords:*** *Deep belief network, Skin diseases, DBN, Deep learning, Neural networks.*

## 1. INTRODUCTION

Significant changes in the environment cause many skin diseases, some of which are life-threatening such as skin cancer, and others are treatable such as Atopic Dermatitis, Dyshidrotic Eczema, Nummular Dermatitis, and others. Therefore, a correct diagnosis of the disease may increase the chances of being cured. To recognize skin diseases, common methods are usually used, such as analysis of clinical data, biopsy tests, blood tests, etc. [2]. Accurate diagnosis has become a difficult issue among experts, so researchers are seeking to use different technologies to provide more efficiency in disease recognition, such as image processing and the use of artificial intelligence techniques, which can be used as an auxiliary tool for the expert to make a diagnosis with high accuracy [3]. Despite the significant challenges in accurately diagnosing skin diseases, the use of artificial intelligence methods, especially deep learning, may be another promising way to increase expertise in medicine[4].. In addition to the presence of a huge amount of information in health centers and clinics that can be exploited using artificial intelligence techniques to diagnose skin diseases because they are considered powerful tools in classifying diseases, many models have been designed that have proven successful in classifying diseases and have achieved high accuracy [5].
Recently, attempts to learn features through supervised or unsupervised learning have increased in popularity. Features are also extracted automatically through machine learning, so no experience is needed in this field, and machine learning can extract a large set of features for the classifier. Many deep learning algorithms are used in image classification that are mainly based on feature extraction, including

convolutional neural networks (CNN) and deep belief networks (DBN). DBN is an advanced generative model that uses deep architecture, used in various fields such as speech recognition, character recognition, facial expressions, medical image analysis, etc. The DBN network is considered a powerful classification tool because it can extract high-level features of learning data and can increase the power of differentiation between different categories in the data [6].

The proposed method includes obtaining images of some skin diseases as a first step, then performing pre-processing on them, after which the images are entered into the DBN network that was built so that the images are classified according to the diseases. The rest of the paper is organized as follows: Section 2 represents a summary of related work, section 3 includes a description of the proposed model in more detail, section 4 shows the results and discussion, and the conclusion and future recommendations are mentioned in section 5.

## 2. RELATED WORK

Deep learning (DL), a rapidly advancing field in artificial intelligence (AI), has demonstrated significant capabilities in image and signal recognition and classification. Skin diseases become widely recognized as a global public health problem [7].

In 2018 Albawi et al. [2] proposed a unique method for identifying three forms of skin diseases: Melanoma, Nevus, and Atypical. Adaptive noise reduction was done by combining Gaussian and average filters during preprocessing to emphasize areas affected by disease. Two-dimensional discrete wavelet transform (2D-DWT) was utilized to extract geometric and texture features. An accuracy of 96.768% was achieved in classification using the International Skin Imaging Collaboration (ISIC) dataset and Convolutional Neural Networks (CNN). A classification algorithm for skin lesions was developed by Alnowami in 2019 [8] using Densely Connected Convolutional Networks (Dense Nets). Normalization and Contrast Limited Adaptive Histogram Equalization (CLAHE) filtering algorithms were used in preprocessing to enhance the local contrast of the images. By utilizing over 30,000 dermatoscopic photos from several open-access sources and employing the proposed algorithm based on the Densely Connected convolutional Networks (Dense Nets) code package for classification, an accuracy of 81.2% was achieved.

In 2019 Mahbod et al. [9] developed a fully automatic skin lesion classification technique using optimized deep features from many well-established CNNs and different abstraction levels. Three pre-trained deep models—AlexNet, VGG16, and ResNet-18, were utilized to generate features for support vector machine classifiers. The 2016–2017 ISIC competition dataset includes 2037 colour dermoscopic skin pictures, including 411 malignant melanoma (MM), 254 seborrheic keratosis (SK), and 1372 benign nevi. A 96.55% accuracy was attained in multiple CNN classifications. Oscar et al. in 2021 [10] involved building software models capable of identifying and categorizing skin cancer. Then, was feature extraction (FE) using 10 distinct pre-trained Convolutional Neural Networks (CNNs). AlexNet combined with a Support Vector Machine (SVM) model achieved an accuracy rate of 90.34% on the HAM10000 dataset, which contains 10,000 images. In 2024 Sulthana et al. [11] proposed a deep learning-based S-MobileNet model to classify 7 types of skin lesions. Utilized a Gaussian filtering technique and Segmentation-based Fractal (SFTA) for feature extraction. The model was used on the HAM10000 dataset, containing 10,000 dermatoscopic images, and achieved an accuracy of 98.345%.

## 3. THE PROPOSED MODEL

Due to differences between skin diseases in terms of appearance, for example, the appearance of a rash or pimples, dry or cracked skin, peeling, etc., in addition to the size of the pimples or spots. Therefore, it is possible to benefit from the prominent and visual features in diagnosing skin diseases, which are extracted from patients' images. Therefore, a model was built consisting of DBN network architecture to recognize

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and classify skin diseases. Images were selected for three types of diseases, such as Atopic Dermatitis, Dyshidrotic Eczema and Nummular Dermatitis. After pre-processing, the images are used as input to the network and appropriate parameters are set to train the network to make the diagnosis more accurate. As shown in figure 1.

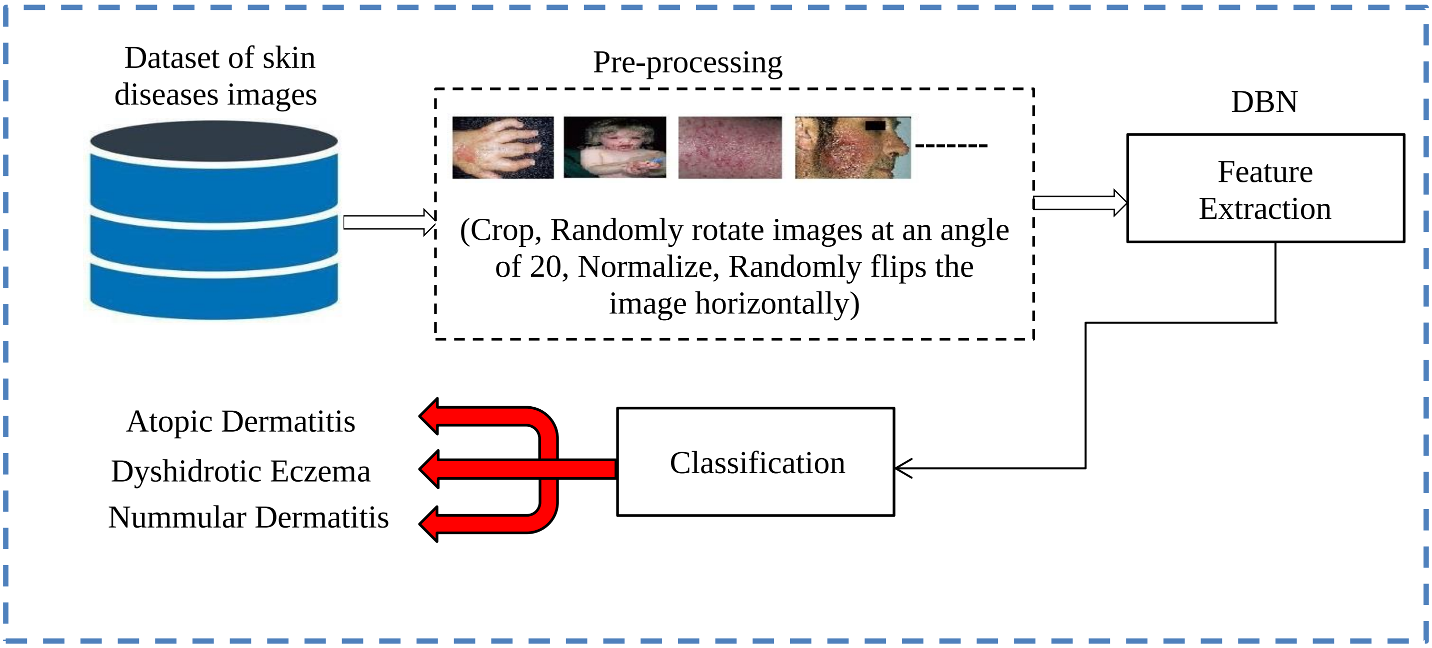


**Figure 1. The proposed model.**

### 3.1. Dataset Preparation

The main goal of the work is to classify skin diseases according to their types using deep learning techniques. The DBN was used to classify three types of diseases Atopic Dermatitis, Dyshidrotic Eczema and Nummular Dermatitis. Therefore, will need a large dataset for these diseases to train the network on them. So, a global dataset, obtained from the Kaggle website was used [12]. The dataset included approximately 1,235 cases of Atopic Dermatitis, 1,300 cases of Dyshidrotic Eczema, and 1,405 cases of Nummular Dermatitis. The images were also duplicated by rotating them at different angles to double the number of images for each disease, and the images included different parts of the body.

### 3.2. Pre-processing

Preprocessing involves several operations performed on dermatology images to obtain greater diagnostic accuracy. The processes included: cropping the image of the disease area, randomly flipping the images horizontally, rotating the images by up to 20 degrees and then converting the image to gray_scale to use as input to the network. Figure 2 shows the preprocessing for several images.

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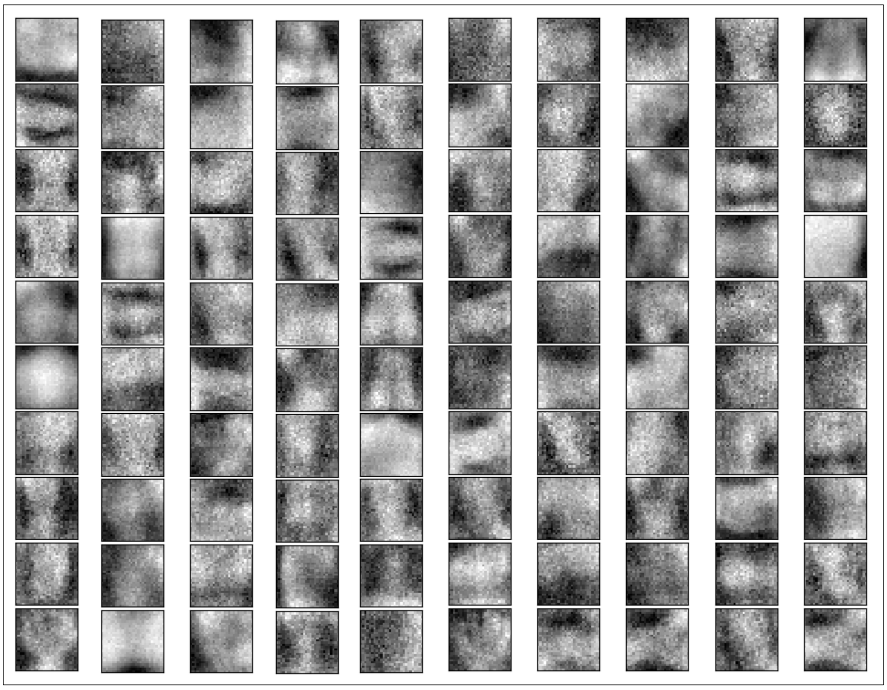

**Figure 2. Some image pre-processing results.**

### 3.3. Apply Deep belief network

To classify skin diseases into three types: Atopic Dermatitis, Dyshidrotic Eczema and Nummular Dermatitis, the DBN deep learning algorithm was used. It is an effective technique for resolving issues in deep layers in neural networks, such as the over-fitting problem in learning and low velocity. DBN is a generative model consisting of layers of random variables, also using Restricted Boltzmann Machines (RBM) [1]. The network is characterized by two properties: the first is to learn the generative weights for each layer from bottom to up, which means that the variables in each layer depend on the top layer, and the second is to infer the values of the latent variables by passing a single vector from the bottom to top, that is, it uses the generative weights in the backpropagation [13].

#### A. Features extraction

Feature extraction is one of the basic and important issues in the classification process, as the performance of the network depends on the features that are learned, which is the reason for making the classification more accurate, especially if it is used in the medical aspect. The DBN in the proposed model contains five layers of RBM to extract features in a hierarchical manner which has proven its efficiency in skin disease classification.

#### B. Restricted Boltzmann Machine (RBM)

RBM generally consists of two layers: the first layer is visible ($\boldsymbol{v}$) and the second layer is hidden ($\boldsymbol{h}$), Each layer contains many nodes [1]. As shown in Figure 3:

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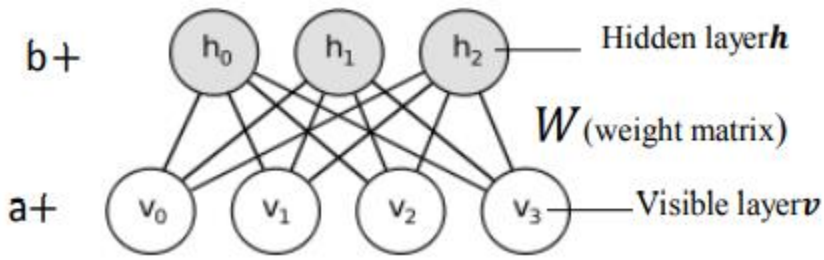


**Figure 3. An example showing the hidden and visible layers of RBM [1] .**

The energy and probability equation are then applied to describe RBM, the state energy $(\boldsymbol{v}, \boldsymbol{h})$ is represented by Equation 1:

$$E_n(v,h,\theta) = -\sum_{i=1}^{D}\sum_{j=1}^{M} W_{ij}\, v_i h_j - \sum_{i=1}^{D} b_i\, v_i - \sum_{j=1}^{M} a_j\, h_j \tag{1}$$

Where $(W, b, a)$ represent the parameters used in the model, the symmetric interaction term between hidden unit $j$ and visible unit $i$ is represented by the symbol $W_{ij}$ [14]. While $b_i$ and $a_j$ are bias. The probability distribution is represented by Equation 2:

$$P(v,h) = \frac{1}{Z}\, e^{-E(v,h)} \tag{2}$$

The visual layer distribution $(\boldsymbol{v})$ can be obtained by summation, as shown in Equation 3:

$$\mathrm{P}(v) = \frac{1}{Z} \sum_h e^{-E(v,h)} \tag{3}$$

Where $\mathrm{P}(v)$) represents the probability function (pdf) for the parameters parameter $\theta \in$ [15]. After initializing the DBN layers, each layer represents RBM, and Figure 4 represents the DBN network architecture [1, 16]. In the proposed model, five layers are used to extract features, as the DBN network is characterized by its high efficiency in extracting additional features, so another layer is added to the soft-max classifier to perform the classification process for skin diseases.

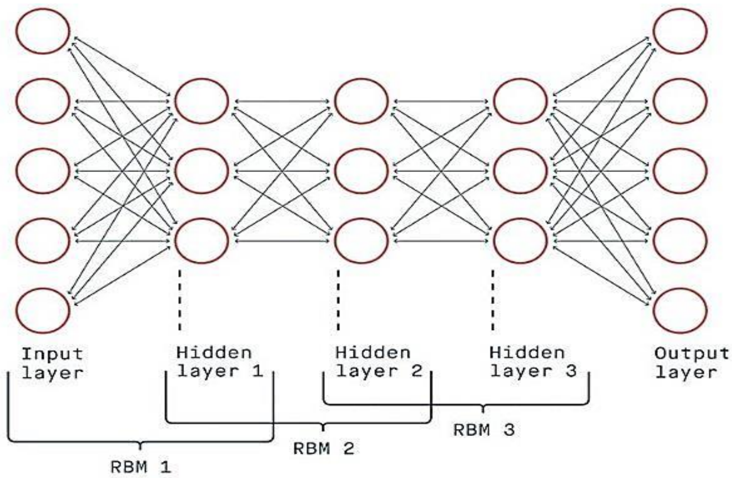


**Figure 4. An Overview of DBN layers [13].**

In the training process, the cost function and gradient descent are calculated. Where Equation 4 represents the cost function:

$$J(\theta) = -\frac{1}{m}\left[\sum_{\mathrm{i}=1}^{\mathrm{m}} \sum_{j=1}^{k} 1\left\{y^{(i)} = j\right\} \log \frac{e^{\theta_j^T x(i)}}{\sum_{i=1}^{k} e^{\theta_j^T x(i)}}\right] \tag{4}$$

Equation 5 shows the gradient-descent:

$$V_{\theta_i} J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[x^{(i)}\left(1\left\{y^{(i)} = j\right\} - p\left(y^{(i)} = j \middle| x^{(i)};\ \theta\right)\right)\right]$$

$$\theta_j\,(n+1) = \theta_j\,(n) + a\nabla\theta_i J(\theta) \tag{5}$$

### C. Softmax Classifier

The soft-max classifier is used as the last layer in the DBN to predict the type of skin disease in the input image, for example, it is (Atopic Dermatitis, Dyshidrotic Eczema and Nummular Dermatitis). Equation 6 represents the general formula of the soft-max function.

$$\mathrm{So}f\mathrm{tmax}(\mathrm{Z_i}) = \frac{exp\ (\mathrm{Z}_i)}{\sum_j exp\ (\mathrm{Z}_i)} \tag{6}$$

### D. Performance Metric

Performance measures are considered very important to evaluate the model in terms of the accuracy of the classifier, so will discuss the most important performance evaluation measures [17, 18], which are as follows:

Recall= $TP/(TP+FN)$ (7)

Precision= $TP/(TP+FP)$ (8)

F1_Score= $2\ *\ (Precision * Recall)/(Precision + Recall)$ (9)

Accuracy= $(TP+TN)/(TP+FN+TN+FP)$ (10)

Where TN: represents True Negative, TP: True Positive, FN: False Negative and FP represents False Positive. The calculation of Recall is determined by Equation (7), which quantifies the degree to which a task has been successfully accomplished. Precision is determined using Equation (8) and serves as a metric for accuracy. The calculation of the F-score is determined by Equation (9), which represents the harmonic mean of precision and recall. Equation (10) calculates classifier accuracy using the four potential outcomes. Classifier accuracy is the percentage of test samples classified correctly.

## 4. EXPERIMENT RESULTS AND DISCUSSION

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After downloading the free dataset from the Kaggle website, which includes many images of skin diseases arranged according to the type of disease, pre-processing was performed on it, which included cropping the disease area from the images and duplicating the number of images for each disease by rotating the images by 20 angles, rotating them horizontally, and resizing them. It is then saved as a new dataset, which is considered an input to the DBN, which is built according to work requirements, as it is designed from five layers of RBM to extract features, then transfer those features to the last layer, which is represented by the SoftMax classifier to perform a classification of skin diseases. It should be noted that after training on the dataset many times, the network structure was adjusted to reach good results.

Figure 5 depicts the training results for the DBN model by plotting the macro average and the weighted average performance, which included recall, precision, and F1 score, which ultimately gives the accuracy of the entire model in classifying the three diseases.

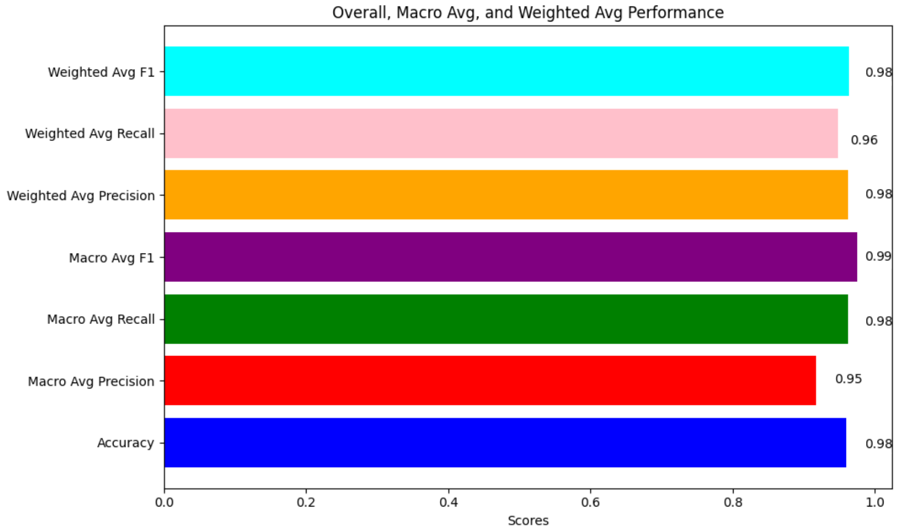


**Figure 5. Training results of the DBN model.**

Also, Figure 6 represents the classification performance of the proposed model, which was obtained after applying the evaluation criteria.

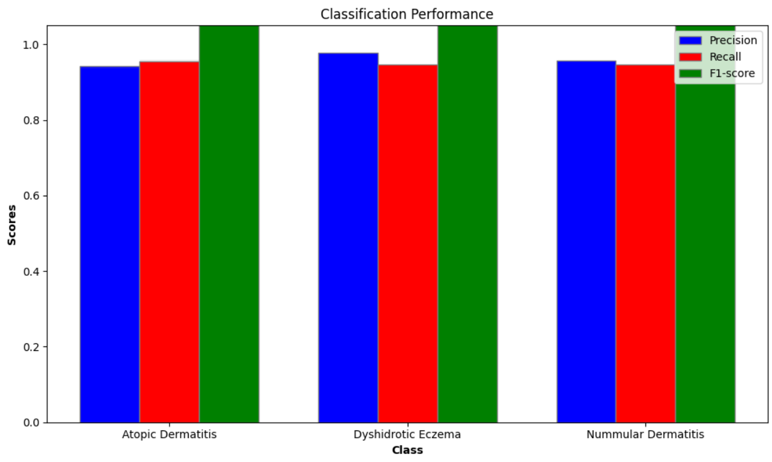


**Figure 6. The classification performance of the proposed.**

 

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After evaluating the model's performance in terms of skin disease classification, a selection of test images is visualized with their expected labels. The model is set to evaluation mode to ensure consistent behaviour during inference. Figure 7 shows some diagnostic results and their comparison with the original images:

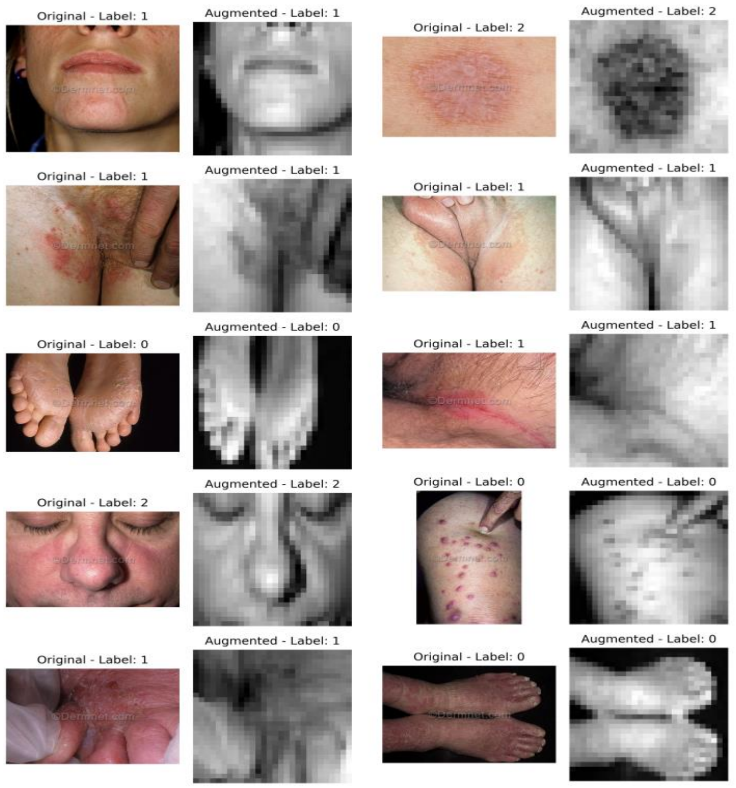


**Figure 7. Shows test results to diagnose skin diseases.**

It is worth noting that the proposed model has been applied to classify other diseases from the Kaggle website, namely Eczema, Psoriasis, and Inea Ringworm Candidiasis. Figure 8 shows the results of the model after making some changes in displaying the results.

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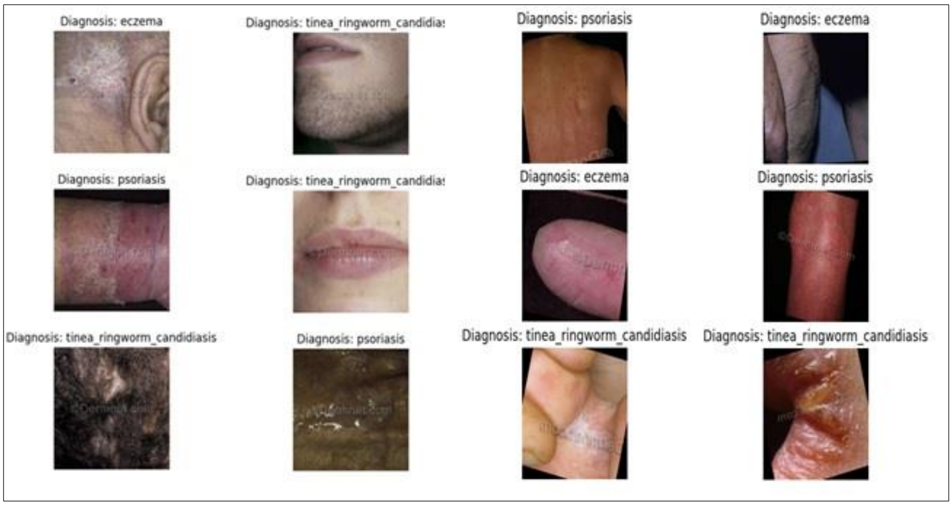


**Figure 8. Shows the results of tests to diagnose other types of skin diseases.**

Table 1 shows a comparison of the proposed study with several recent studies.

**Table 1.** Comparison of the proposed method with other techniques

| **Ref** | Year | Feature extraction methods | Datasets | Machine Learning Methods | Accuracy |
|---|---|---|---|---|---|
| **[2]** | 2018 | Gaussian, average filters and 2D-DWT | ISIC dataset | CNN | 96.768% |
| **[8]** | 2019 | Normalization and CLAHE filtering | 30,000 dermatoscopic photos from several open-access sources | Dense Nets | 81.2% |
| **[9]** | 2019 | AlexNet, VGG16, and ResNet-18 | 2016–2017 ISIC competition dataset includes 2037 colour dermoscopic skin pictures | CNN+SVM | 96.55% |
| **[10]** | 2021 | 10 distinct pre-trained Convolutional Neural Networks (CNNs) | HAM10000 dataset, which contains 10,000 images | AlexNet+SVM | 90.34% |
| **[11]** | 2024 | Gaussian filtering technique and Segmentation-based Fractal (SFTA) | HAM10000 dataset, containing 10,000 dermatoscopic images | Deep learning-based S-MobileNet model | 98.345% |
| Proposed model | | Constrained Boltzmann machine (RBM) | Kaggle dataset 2,289 images | DBN | 98.773 |

## 5. CONCLUSIONS

This paper sought to propose a model for diagnosing skin illnesses, including human life-threatening, via a deep belief network. This network is characterized by high accuracy because it consists of several layers, each layer representing unsupervised RBM, and each hidden layer's outputs are inputs to the visible upper layer. Therefore, this process aids in obtaining more extensive additional features from the original sample set, enhancing the network's capability in feature extraction. The Soft-max classifier was utilized to accurately classify the three skin illnesses. In the future, it may be feasible to train the new model on other illness categories or utilise alternative classifiers to achieve higher accuracy.

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