[1]Atul Pawar

G.B Sambare

Shreya Mande

Dhanali Kathe

Vaishnavi Mande

Maithili Sude

Classification of Different Types of Psoriasis using CNN

Abstract: Psoriasis is a chronic disease in which excessive immune activity leads to excessive skin cell proliferation. The initiative aims to solve this critical issue Rapid skin cell turnover, which happens every 3 to 7 days as opposed to the typical 3 to 4 weeks, is the cause of this disorder. Its onset is influenced by various factors, including infections, stress, and heredity. It is not contagious. Elbows, knees, and scalp are the most common places for scaly, inflammatory skin patches to appear, but other body areas may also be affected. A rash with itchy, scaly patches is the result of the skin condition psoriasis. Over 125 million people worldwide—roughly 2% to 3% of the population—have psoriasis. Psoriasis comes in different forms, including nail psoriasis, erythrodermic psoriasis, pustular psoriasis, inverse psoriasis, and plaque psoriasis. Psoriasis is a skin disorder that affects 296 people; of these, 175 (59.1%) are Malay people, 82 (22.7%) are Indians, 37 (12.5%) are Chinese, and 2 (0.6%) are other people. The majority of clinical cases (89.9%) are caused by chronic plaque psoriasis, with the remaining cases being caused by erythrodermic psoriasis (4.7%), guttate psoriasis (3.0%), and pustular psoriasis (1.7%) in that order of prevalence [18]. Using machine learning approaches, this study aims to accurately classify several forms of psoriasis, such as plaque, guttate, nail, erythrodermic, pustular, inverse and normal psoriasis. The goal is to create a reliable classification technique that can use image data to discern between these different types of psoriasis. In order to do this, deep learning models called convolutional neural networks, or CNNs, are used. CNNs are particularly well-suited for picture categorization tasks. For efficient categorization across all classes in this study, the CNN algorithm is used. Data augmentation and transfer learning are the methods used. We take the affected image as input and determine the type of psoriasis from the output.

Keywords: Skin Disease ,Types of Psoriasis ,Deep Learning ,CNN

1 Introduction

Psoriasis is a chronic inflammatory skin condition that affects people all over the world. It has a major influence on healthcare costs and quality of life. Psoriasis are of various types, such as pustular, erythrodermic, inverse, plaque, and nail. Accurate diagnosis and classification of these types is crucial for efficient patient care and individualized treatment plans. To differentiate between different forms of psoriasis, dermatologists have always relied on clinical judgment and visual investigation. But because of its subjectivity, this procedure may result in inconsistent diagnoses and possibly postpone necessary measures. Psoriasis and other dermatological conditions may now be automatically and objectively classified thanks to advancements in deep learning and artificial intelligence (AI), especially Convolutional Neural Networks (CNNs), which have completely changed medical image analysis in recent years. Data augmentation, transfer learning are the methods used.

Skin's characteristic red spots that can cause pain, scaliness, and itching are what make it unique. Psoriasis is an autoimmune skin ailment that is believed to be caused by the immune system destroying healthy skin cells. Psoriasis is assumed to be influenced by both genetics and environmental factors, while the exact aetiology is unknown. It all starts when skin cells are attacked by the body's immune system, which disrupts their normal cycle

[1] [1] Department of Computer Engineering, Pimpri Chinchwad college of Engineering , Pune, India

*Corresponding author e-mail: atul.pawar@pccoepune.org

santosh.sambare@pccoepune.org

shreyamande06@gmail.com

dhanalikathe16@gmail.com

vaishnavimande3@gmail.com

maithilisude19@gmail.com

of development and survival. These extra skin cells in psoriasis lesions result in thick, red, puffy, itchy patches that gradually migrate to different parts of the body. The body may be partially or completely covered in these lesions.

Dermatologists usually identify the precise type of psoriasis by general observation and biopsies. However, the uncertainty surrounding the number of tests needed to accurately identify the correct kind of psoriasis highlights the shortcomings of the diagnosis techniques now in use. Psoriasis comes in several forms and with various traits, such as Plaque, Guttate, Inverse, Erythrodermic, Inverse, Nail psoriasis [5–6]. The most prevalent kind of psoriasis, known as plaque psoriasis, accounts for 85% of all skin diseases. Plaque psoriasis affects 2–6% of Malaysians, according to the Dermatological Society of Malaysia [7].

In this study, we offer a CNN-based method for automatically classifying different kinds of psoriasis using dermatological photos. Our suggested solution intends to use deep learning to deliver precise and reliable classification findings, helping dermatologists to make well-informed decisions about patient care and treatment strategies.

Our study uses a carefully selected dataset of different kinds of psoriasis photos that we got from Google to fulfil the requirement for a reliable and efficient automated classification method. The CNN model can accurately discriminate between nail psoriasis, guttate, inverse, erythrodermic, pustular, and plaque psoriasis since it has been trained to recognize complex patterns and features.

2. Literature Review

Numerous researchers were involved in the categorization of psoriasis types. They used a variety of computer vision techniques, such as image processing, segmentation, feature extraction, and image classification. These methods are also applied in other research studies.

In [22], Long short-term memories (LSTMs) and convolutional neural networks (CNNs) are two deep learning techniques that the authors used. The models were trained using dermoscopic image data from the HAM1000 database, which is accessible to the general public. When classifying skin images into the five categories of psoriasis and normal skin, the CNN model performed better than the LSTM model. With an accuracy of 84.2%, the CNN outperformed the LSTM with a 72.3% accuracy. Although the study's diversity and clinical relevance may be limited, the authors acknowledge that the study is based on a publicly available dataset. In order to overcome the drawback of using publicly accessible datasets, the authors propose that future research should incorporate images that have been collected clinically in order to improve the classification models' robustness.

In [18], The researchers classified photos from the Derma Net website into categories for psoriasis and normal skin using a CNN. They used accuracy as a metric to assess the CNN model's performance. CNN attained a 77.65% accuracy rate. The study's shortcomings, such as its small sample size and unequal class distribution, are acknowledged by the authors. The findings might not be as broadly applicable given the small sample size of 77. In addition, there were more pictures of normal skin than psoriatic skin in the class distribution, which was unbalanced. This might have increased the model's precision in classifying normal skin. The authors propose that by adjusting the parameters in the CNN's pooling and fully connected layers, more study is necessary to increase the model's generalizability.

In [19], The authors suggest a new deep learning strategy dubbed Derma Care to overcome the drawbacks of earlier techniques. Derma Care was trained on an augmented dataset to increase accuracy and has the capacity to identify multiple skin conditions at once. The Derma Care model classified eczema and psoriasis skin conditions with an overall accuracy of 96.24%. The model's performance was assessed using a number of metrics, such as F1-score, recall, accuracy, and precision. To find out how Derma Care performs on a bigger and more varied dataset, more research is required. It would also be helpful to know how the model functions in a clinical context.

In [28], The researchers classified pictures from a dataset into six groups using a pre-trained CNN model called Mobile Net: plaque, guttate, inverse, pustular, erythrodermic psoriasis, and normal skin. The CNN classified the six types of psoriasis with an accuracy rate of 89%.The pre-trained model used in the study, which may not be ideal for the task of classifying psoriasis, is acknowledged by the authors. Furthermore, they make no mention of the quantity or origin of the dataset that was used to train and evaluate the model. The results imply that CNNs may be able to accurately classify various forms of psoriasis. To investigate the use of CNN models that have been fine-tuned and to look into how well they perform on larger and more varied datasets, more research is necessary.

In [25], To increase the precision of classifying the severity of psoriasis, the researchers suggested a deep learning technique that integrates a hierarchical multi-scale deformable attention module (MS-DAM). Within the psoriasis lesions, the model is assisted by MS-DAM in identifying representative regions of irregular shapes and sizes. To make the model more resilient to changes in psoriasis presentations, they also trained it on a dataset of images that had artificially enlarged variations in severity levels. An F1-score of 0.93 was obtained by the suggested method, indicating good performance in psoriasis severity classification. When the researchers compared MS-DAM's accuracy to other self-attention techniques already in use, they discovered that it performed better.

3. Research Methodology

3.1. Input Images

The dataset comprises 1605 distinct types of psoriasis images, including those with normal skin. The types of psoriasis include erythrodermic psoriasis, plaque psoriasis, inverse psoriasis, pustular psoriasis, guttate psoriasis and nail psoriasis. But by applying data augmentation images the number has increased.

1. Plaque psoriasis: There are 461 images of plaque. The most typical kind of psoriasis is called plaque psoriasis. It is characterized by red, elevated areas of skin that are covered in scales, or a silvery-white accumulation of dead skin cells. Plaques are these patches that can cause pain and itching.

2. Guttate psoriasis: 315 images of guttate is used in this. The skin develops tiny, drop-like lesions that are characteristic of guttate psoriasis. It frequently happens all of a sudden and is usually brought on by bacterial infections, like strep throat. In children and young adults, it is more prevalent.

3. Inverse psoriasis: 273 images of inverse are present .Skin folds like those under the breasts, in the thighs, and under the armpits are the main areas affected by inverse psoriasis. It manifests as red, smooth lesions devoid of the usual scales, unlike plaque psoriasis. Sweating and friction both have the potential to make it worse.

4. Pustular psoriasis: There are 177 images of pustular psoriasis. The presence of pus-filled blisters, or pustules, encircled by red skin is a characteristic of pustular psoriasis. The skin surrounding the pustules is frequently red and tender, and it can be localized or widespread. Some medications or other factors may cause this kind of psoriasis.

5. Erythrodermic Psoriasis: Total 205 images are present. This severe and uncommon type of psoriasis can entail the whole body. Skin shedding occurs in sheets, and there is generalized redness and inflammation. Because of the seriousness of the condition, you might need to see a doctor right away.

6. Nail Psoriasis :560 images of nail psoriasis are present in the dataset When psoriasis infects the nails, it is known as nail psoriasis. Psoriasis is a long-term autoimmune condition that mostly affects the skin; however, it can also grow into the nails.

7. Normal Skin :124 images of normal skin are also present in the dataset. This is the normal, healthy state of the skin, free of any psoriasis or other skin problem indications or symptoms.

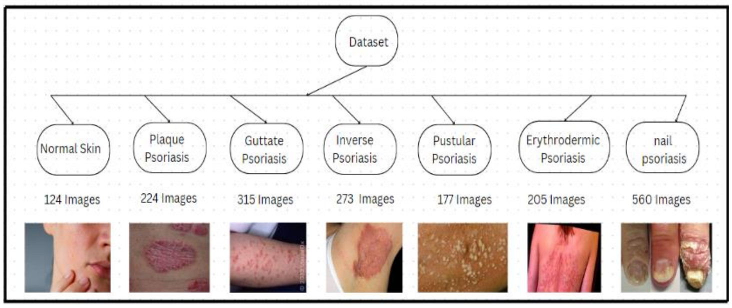

Figure 1. Dataset

3.2. Data Splitting

Data is divided into validation, testing, and training categories.15% data is used for testing and remaining is used for the training.

3.3 Convolutional Neural Network (CNN)

A particular kind of artificial neural network is the convolutional neural network (CNN) model (ANN). It is important in the classification of images. Different layers comprise a convolutional neural network. Activation Function (ReLU Function), Normalization layer, flatten layer, Dense layers, Dropout layers, Convolutional Layer (like conv2D), Pooling Layers (like MaxPooling2D), and Normalization Layer are some of the layers (Figure 2). All of these layers work together to optimize CNN's design for a particular task. Psoriasis can be categorized into several categories by utilizing all of these layers' combinations.

In neural network training, however, it might be challenging to determine how many epochs to utilize. When a network has too much specialized learning from the training dataset, but too many epochs are used to detect new data, this is known as overfitting of the training dataset. Alternatively, the training dataset may become underfitted if there are not enough epochs, which would hinder the network's ability to recognize the underlying patterns in the data. To ensure our model could perform well on the training dataset and well-generalize to new data, we had to carefully balance the number of training epochs.

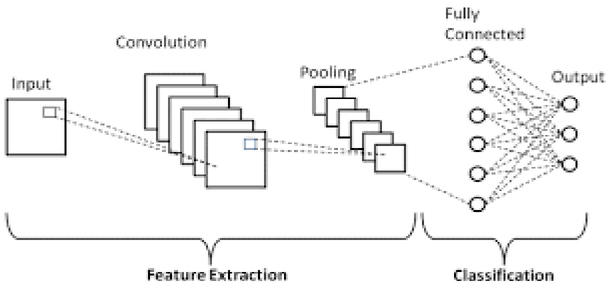

Figure 2. Basic Structure of CNN

3.2.1 Convolutional Layer

A convolutional layer is an essential building element of convolutional neural networks (CNNs), a type of deep learning model that is widely utilized for image processing and recognition applications. Feature extraction from input data, such images, is the primary goal of a convolutional layer. The primary function of a convolutional layer is convolution. In this procedure, a tiny filter called a kernel is slid across the incoming data. The pooling layer comes after the convolutional layer, which is made up of numerous filters, each with its own feature map and other parameters like filter size, padding, and activation function. First, a 2D convolutional layer is used, with 8 filters, a kernel size of (3,3), valid padding, a ReLu activation function, and an input shape of (224,224,3), denoting an image with 224 x 224 pixels as its input size.

3.3.2 Pooling Layer

A type of layer called a pooling layer is commonly employed in convolutional neural networks (CNNs) to decrease the spatial dimensions of feature maps while retaining important information. It aids in lowering computing complexity and controlling overfitting. During the pooling operation, a pooling window is slid across the input feature map in a predefined stride. By combining data from the window's covered region, the pooling window lowers the spatial dimensions of the output feature map at each location. The reduced-size feature map is obtained by later layers (such convolutional or fully connected layers) for further processing. Pooling layers are typically implemented after convolutional layers in feature maps to progressively reduce the spatial dimensions while retaining important characteristics.

3.3.3 Fully connected layer (FCL)

CNN uses a fully connected layer (FCL) or many FLCs to classify data. All nodes in a forward-coupling layer (FCL) are directly connected to all other nodes in consecutive layers. By utilizing the output of the CL and PL processes, new features are extracted from the image. The input image is then classified into several groups by FCL using features based on the training dataset. FCL does not store any spatial information.

4. Architecture Diagram

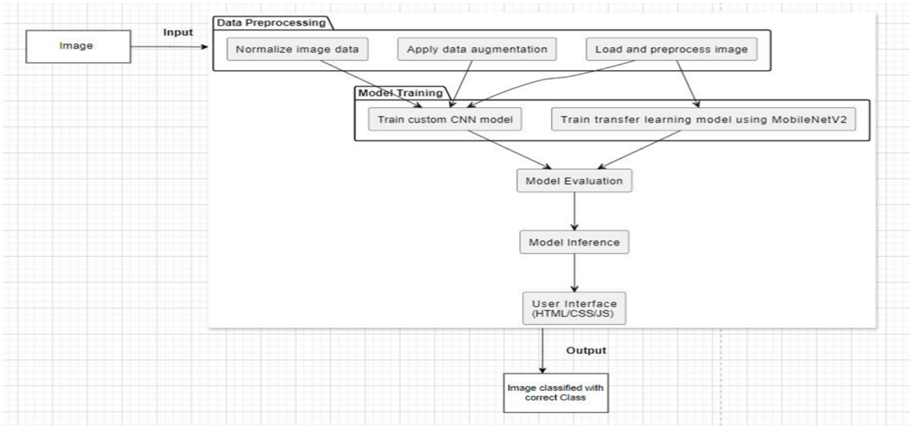

Figure 3. Architecture Diagram

4.1 Input

Several kinds of psoriasis images

4.2 Preparing data

The data that will be fed into the model must be prepared at this step.

It consists of:

- Load and preprocess picture data: This probably means to load the image data from a file location or folder, and then to manipulate the images by resizing, converting to the right format, or in other ways.
- Normalize picture data: This stage involves scaling each image's pixel intensity within a predetermined range. In training, this facilitates a faster convergence of the model.
- Apply data augmentation: Techniques like random cropping, flipping, or rotating the images can help create artificial variations of the training data. This reduces the possibility that the model may overfit the particular training set.

4.3 Training Models

Here, the pre-processed data is used to train the model.

- Train custom CNN model: This is the process of creating a CNN model from the ground up with Python packages such as Keras or TensorFlow. Hyperparameter tuning and a thorough understanding of CNN architectures would be necessary for this.
- Train the MobileNetV2 transfer learning model: This method starts with a pre-trained model, such as MobileNetV2. Usually, just the last layers of the pre-trained model are adjusted using the current dataset; the weights of the model are left unchanged. This is a quicker and frequently more successful method, particularly with smaller datasets.

4.4 Model Evaluation

To determine the model's efficiency on unseen data, its performance is assessed on a validation set, which is a different dataset, following training.

4.5 Interface from the Model

Model is Integrated with a web application.

4.6 User Interface

(JS, CSS, and HTML):

Creating a user interface to communicate with the trained model is the focus of this step. Web development tools like HTML, CSS, and JavaScript are frequently used to build web pages that can receive input from users, process it through a model, and display the output. When we give a input image it will show the output of which type of psoriasis it is.

4.7 Output

Classified which type of psoriasis image it is.

5. Mathematical Model

Mathematical Model of the Convolutional Neural Network

A set of equations encapsulating the functions carried out at each layer can serve as the mathematical model for this CNN.

Below is an explanation of the mathematical processes underlying every layer in the model:

5.1 Layer of Input

No mathematical operations take place in the input layer. It just accepts an input image with the dimensions {(img_height, img_width, 3)}. Here,

- {img_height}: The pixel height of the input picture.
- {img_width}: Pixel-wise width of the input picture.
- {3}: The quantity of channels (RGB).

5.2 Convolution Layer (Conv2D)

The layers used for convolution employ a `3x3' filter (kernel) to adjust the input image's width and height. The filter applies a dot product (element-wise multiplication and summation) between the filter weights and the corresponding elements in the input image as it moves one pixel at a time across the image with a stride of 1. The 'Same' padding makes sure that the dimensions of the output and input are the same. Mathematically, the procedure can be expressed as follows for each output location {(i, j)} in the feature map:

Output[i, j] = ReLU(Σ W[k, l] * Input[i + k - 1, j + l - 1] + b)

- {W}: Filter weights (each filter represented as a 3x3 matrix).
- {b}: The filter's bias term.
- Iterators for the filter, {k, l}
- The Activation function {ReLU} is a Rectified Linear Unit that produces the input and the element-wise maximum of 0.

5.3 Layers of Pooling (MaxPooling2D)

Taking the maximum value within a certain window (in this case, 2x2) across the width and height dimensions, the pooling layers down sample the output of the convolutional layers. This lowers the data's dimensionality and aids in preventing overfitting. Pooling layers do not have any learnable parameters.

1. Flatten Layer:

The convolutional layers' multi-dimensional feature maps are converted into a single-dimensional vector by the flatten layer. The data can now be fed into the layers that are fully connected.

2.The fully-connected layers

The fully-connected layers resemble the layers of a conventional neural network. They first multiply the input vector by the weight matrix, then apply an activation function (in this case, ReLU). The convolutional layers extract features, and this layer aids in the learning of more intricate correlations between those features. In terms of mathematics, every neuron {j} in the fully-connected layer is:

ReLU(Σ Input[i] * W[i, j] + b) = Output[j]

- W: The layer's weight matrix.
- b: Layer's bias vector

3.Output Layer:

The output size of the last dense layer is equal to {num_classes}. Additionally, it makes use of a softmax activation function, which converts the output values from 0 to 1 into probabilities for each class. As the output, the class with the highest likelihood is anticipated.

Overall Model

When an input image {X} is given, the CNN model as a whole can be understood as a function that produces a probability distribution across the class labels {P(y | X)}. The different layer processes mentioned above can be combined to create a mathematical representation of this function.

6. Result and Output

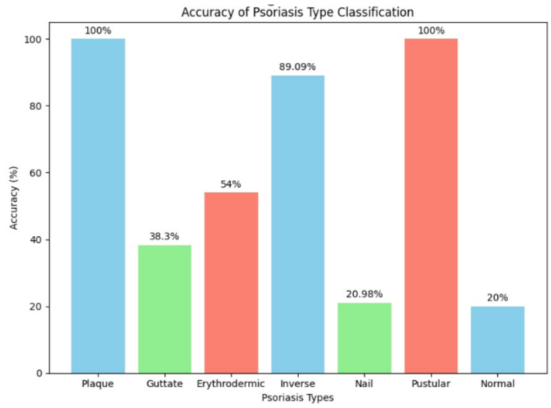

Figure 4. Accuracy of psoriasis type classification

This graph represents the accuracy of all single classes calculated separately. It a bar graph which contain plaque, guttate, erythrodermic, Inverse, pustular, Normal skin types of psoriasis.

x-axis: x -axis represents accuracy of the CNN model.

y-axis: y-axis represents types of psoriasis i.e. plaque, guttate, erythrodermic, Inverse, pustular, Normal skin

Plaque and Pustular has the highest accuracy i.e. 100%, Lowest accuracy we get is of Normal skin images that is 20%. Nail images has accuracy of 20.98 %. Inverse has 89.09%, guttate has accuracy of 38.3% and erythrodermic images has accuracy of 54%.

Hence these are the accuracy of different types of psoriasis image which is calculated separately.

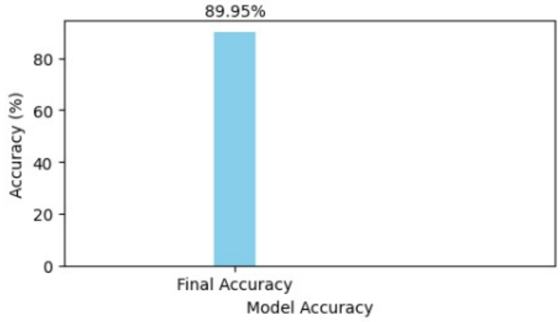

Figure 5. Model Accuracy

This graph represents the accuracy of CNN model. X-axis represent the accuracy in percentages while Y- axis represents the model i.e. CNN.

Above graph contains the accuracy of all dataset this contain all types of classes.

We have 7 classes i.e. plaque, guttate, erythrodermic, Inverse, pustular, Normal skin

By using the CNN model, we get the 89.95 % accuracy.

This gives us the output of various psoriasis types that have been classified. There are five different forms of psoriasis: nail, erythrodermic, pustular, inverse, and plaque. Figure 6 Shows the class Erythrodermic is classified when we give the input image and upload it on web application.

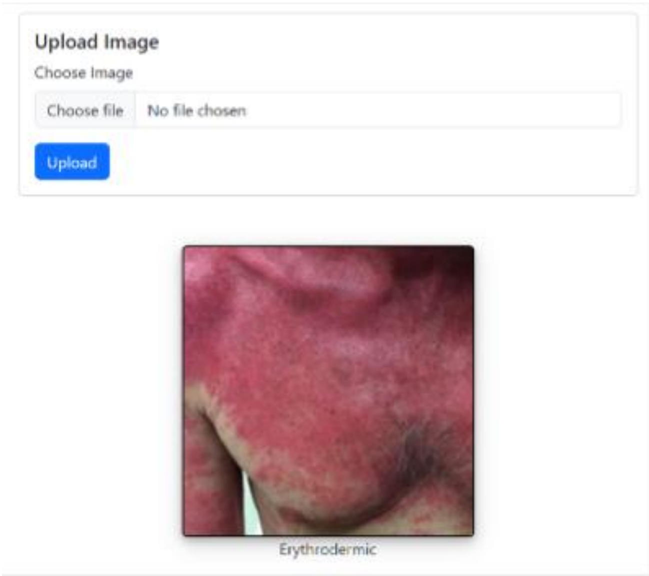

Figure 6. Classification of erythrodermic psoriasis

7. Conclusion and future Work

The six types of psoriasis and normal skin were categorized using a deep learning classification technique in this study. These six types of psoriasis are nail, erythrodermic, pustular, guttate, inverted, and plaque.

The convolutional neural network (CNN) and its application demonstrated an accuracy of 89.95 % after the colour, texture, and shape features were extracted. The model is also integrated with the web application. Selected image is being uploaded and the result we get the classified psoriasis type. This accuracy shows that the suggested deep learning application is dependable and efficient. There are research implications for this proposed deep learning application that could lead to improvements in biological imaging techniques.

References

[1] Fadzil M. H. A., Ihtatho D., Affandi A. M., Hussein S. H. Area assessment of psoriasis lesions for PASI scoring. *Journal of Medical Engineering and Technology* . 2009;33(6):426–436. doi: 10.1080/07434610902744066. [PubMed] [CrossRef] [Google Scholar] [Ref list].

[2] Yadav N, Yadav N, Narang VK. Skin diseases detection models using image processing: A survey. International Journal of Computer Applications. 137(12):0034-9, 2016.

[3] Dhandra B, Soma S, Reddy S, Mukarambi G. Color Histogram Approach for Analysis of Psoriasis Skin Disease. InInt. Conf. on Multimedia Processing 2013.

[4] Rendon A., Schäkel K. Psoriasis pathogenesis and treatment. *International Journal of Molecular Sciences* . 2019;20(6):p. 1475. doi: 10.3390/ijms20061475. [PMC free article] [PubMed] [CrossRef] [Google Scholar] [Ref list]

[5] Shrivastava VK, Londhe ND, Sonawane RS, Suri JS. Reliable and accurate psoriasis disease classification in dermatology images using comprehensive feature space in machine learning paradigm. Expert Systems with Applications. 42(15-16):6184-95, 2015

[6] Shrivastava VK, Londhe ND, Sonawane RS, Suri JS. Computer-aided diagnosis of psoriasis skin images with HOS, texture and color features: a first comparative study of its kind. Computer methods and programs in biomedicine. 126:98-109,2016.

[7] MohdAffandi A, Khan I, NgahSaaya N. Epidemiology and Clinical Features of Adult Patients with Psoriasis in Malaysia: 10-Year Review from the Malaysian Psoriasis Registry (2007–2016). Dermatology research and practice. 2018.

[8] Sun L., Zhang S., Chen H., Luo L. Brain tumor segmentation and survival prediction using multimodal MRI scans with deep learning. *Frontiers in Neuroscience* . 2019;13:p. 810. doi: 10.3389/fnins.2019.00810. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[9] DermNet NZ. Cysts. DermNet NZ website.

[10] Shrivastava VK, Londhe ND, Sonawane RS, Suri JS. Reliable and accurate psoriasis disease classification in dermatology images using comprehensive feature space in machine learning paradigm. Expert Systems with Applications. 42(15-16):6184-95, 2015.

[11] M. N. Alam, T. T. K. Munia, K. Tavakolian, F. Vasefi, N. MacKinnon and R. Fazel-Rezai, "Automatic detection and severity measurement of eczema using image processing," 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2016, pp. 1365-1368, doi: 10.1109/EMBC.2016.7590961.

[12] Parvathaneni Naga Srinivasu 1,† , Jalluri Gnana SivaSai 2 , Muhammad Fazal Ijaz 3,† , Akash Kumar Bhoi 4 , Wonjoon Kim 5,* and James Jin Kang 6,* Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM, Sensors 2021, 21(8), 2852.

[13] Yadav, Nisha, Virender Kumar Narang, and Utpal Shrivastava. "Skin Diseases Detection Models using Image Processing: A Survey", International Journal of Computer Applications 137, no. 12 (2016).

[14] Kumar, VinayshekharBannihatti, Sujay S. Kumar, and Varun Saboo. "Dermatological disease detection using image processing and machine learning." In Artificial Intelligence and Pattern Recognition (AIPR), International Conference on, pp. 1-6. IEEE, 2016.

[15] Revathi, V., and A. Chithra, "A Review On Segmentation Techniques In Skin Lesion Images", Intl Research Journal of Engg and Tech (IRJET) 2, no. 09 (2015).

[16] Balipa, Mamatha. "OPINION ANALYSIS OF TREATMENTS FROM ONLINE HEALTHCARE FORUMS FOR THE DISEASE PSORIASIS USING NLP AND ARTIFICIAL NEURAL NETWORK." Development 5, no. 07 (2018).

[17] T.R.Arunkumar, Dr. H.S.Jayanna "Classification of different types of psoriasis using machine learning" , JETIR, volume 6 , Issue 6 , 2019.

[18] Rosniza Roslan, Iman, Nurbaity Sabri, Zaidah Ibrahim "Evalution of psoriasis skin disease classification using convolutional neural network" , IAES Vol. 9 (2020).

[19] Mohamed Hammad , Pawel Plawiak , Mohammed ElAffendi, Ahmed, Asmaa, "Enchanced Deep Learning Approach for accurate Eczema andPsoriasis Skin Detection" , Sensors (2023).

[20] Jian-Ming Syu, Chun Hao Lai, Guo Shiang Lin, Sin Kuo Chai , "Psoriais Detection Based on Deep Neural Network" , IEEE (2018).

[21] George Y., Aldeen M., Garnavi R. A pixel-based skin segmentation in psoriasis images using committee of machine learning classifiers. Proceedings of the 2017 International Conference On Digital Image Computing: Techniques and Applications (DICTA); December 2017; Sydney, Australia. pp. 1–8. [CrossRef] [Google Scholar].

[22] Syeda Fatima Aijaz , Saad Jawaid Khan, Fahad Azim , Choudhary Sobhan Shakeel and Umer Hassan " Deep learning Application for effective Classification of different Types of Psoriasis " ,nNational Library of medicine 2022.

[23] Kassem M. A., Hosny K. M., Damaševičius R., Eltoukhy M. M. Machine learning and deep learning methods for skin lesion classification and diagnosis:a systematic review. *Diagnostics* . 2021;11(8):p. 1390. doi: 10.3390/diagnostics11081390. [PMC free article] [PubMed] [CrossRef] [Google Scholar] [Ref list].

[24] Moon C.-I., Lee J., Yoo H., Baek Y., Lee O. Optimization of psoriasis assessment system based on patch images. *Scientific Reports* . 2021;11(1):1–13. doi: 10.1038/s41598-021-97211-9. [PMC free article] [PubMed] [CrossRef] [Google Scholar] [Ref list].

[25] Cho-I.Moon , Jiwon Lee, Yoo Sang Baek & Onesok Lee Psoriasis severity classification based on adaptive multi-scale features for multi-severity disease ,Scientific Reports, 13:17331,2023.

[26] Zhou, J.; Li, Y.; Guo, X. Predicting psoriasis using routine laboratory tests with random forest. PLoS ONE 2021, 16, e0258768. [CrossRef].

[27] AlDera, S.A.; Othman, M.T.B. A model for classification and diagnosis of skin disease using machine learning and image processing techniques. Int. J. Adv. Comput. Sci. Appl. 2022, 13. [CrossRef].

[28] Hameed, N.; Shabut, A.M.; Ghosh, M.K.; Hossain, M.A. Multi-class multi-level classification algorithm for skin lesions classification using machine learning techniques. Expert Syst. Appl. 2020, 141, 112961. [CrossRef].

[29] Li, Z.; Koban, K.C.; Schenck, T.L.; Giunta, R.E.; Li, Q.; Sun, Y. Artificial intelligence in dermatology image analysis: Current developments and future trends. J. Clin. Med. 2022, 11, 6826. [CrossRef].

[30] A. Dawadikar, A. Srivastava, N. Shelar, G. Gaikwad and A. Pawar, "Survey of Techniques for Pulmonary Disease Classification using Deep Learning," 2022 IEEE 7th International conference for Convergence in Technology (I2CT), Mumbai, India, 2022, pp. 1-5, doi: 10.1109/I2CT54291.2022.9824879.