

Skin Disease Detection using Convolutional Neural Network: A Hybrid Approach Combining Image Preprocessing and Feature Extraction Techniques

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Abstract—A persistent inflammatory skin condition called psoriasis results in red, white, and scaly areas of skin. The Psoriasis Area and Severity Index (PASI), which is calculated, is often used to determine the severity of psoriasis. The severity of the erythema parameter is classified subjectively by doctors into many levels. The ability to diagnose and categorise psoriasis using simply clinical evaluation is, however, constrained. Convolutional neural networks (CNN) powered by deep learning have recently made advancements that have increased the accuracy of illness categorization. Therefore, the goal of this work is to classify and identify the erythema of psoriasis lesions using CNN architectures, especially CNN and ResNet 50. These two skin illnesses are eczema and psoriasis. A 10-fold cross-validation was performed to examine the performance of five distinct cutting-edge CNN architectures. The analysis reveals that the Kirsch's template and Inception ResNet 50 architecture combined for a maximum validation accuracy of 98.4%. The suggested approach may be used to quantitatively evaluate the erythema of a psoriasis lesion, and the performance matrices indicate that it performs very well in terms of diagnosing skin conditions. With limited restrictions on the acquisition technique, the proposed strategy has the potential to be an affordable, quick, reliable, and simple method in a dermatological setting.

Index Terms— Psoriasis Disease, Resnet-50, Kirsch's Template, Image Processing Techniques

I. INTRODUCTION

Skin cancer, especially melanoma, is estimated to be the fastest growing cancer in many countries around the world. It is important to detect and treat these skin disorders accurately because it can indicate the presence of malignancy [1]. Deep learning comes into play here. Convolutional Neural Networks (CNN) are a sort of machine learning technology that is used in deep learning to learn and carry out challenging tasks. Deep learning has been applied in

the medical industry for a number of purposes, including the diagnosis of skin malignancies. The goal of this study is to assess how well a deep learning model performs in detecting and classifying the red rash that is frequently seen in psoriasis lesions, or erythema. A widespread skin disorder, psoriasis affects 2-3% of the global population [2]. It happens when the immune system assaults the skin cells and speeds up their growth. Although psoriasis is not deadly, it may nevertheless be quite painful and uncomfortable. Symptoms may be controlled with the use of topical steroids or other medicines [3]. To make sure that patients receive early treatment, an accurate diagnosis must be made. The Inception ResNet 50 architecture with Kirsch's template was employed in this work since its efficacy in the identification and categorization of skin cancer has been demonstrated [4]. The findings of a 10-fold cross validation analysis of this model's performance are encouraging. The performance matrices indicate that the suggested approach performs considerably well in terms of diagnosing skin illnesses, and it may be used to objectively evaluate the erythema of a psoriasis lesion [5]. With limited restrictions on the acquisition technique, the proposed strategy has the potential to be an affordable, quick, reliable, and simple method in a dermatological setting. Therefore, this study can help dermatologists to accurately diagnose skin disorders, ensuring that patients receive timely treatment and a better quality of life [6]. Psoriasis, while a non-reversible disease, can be managed effectively with early diagnosis and appropriate treatment. The diagnosis of psoriasis can be challenging due to its complex pathophysiology, and physicians must consider various factors such as clinical presentation, family history, and other related conditions [7]. It is important to identify the specific type of psoriasis the patient is suffering from, including psoriasis vulgaris, psoriasis arthropatica, or erythrodermic psoriasis. There are several ways to

accurately diagnose psoriasis, including physical examination, diagnostic imaging, and laboratory testing. According to the severity of the condition, psoriasis is often treated using a mix of topical and systemic medications [8]. To stop disease development and flare-ups, long-term follow-up and monitoring are crucial. The area of medical imaging, including radiology, dermatology, and ophthalmology, has embraced deep learning, especially convolutional neural networks, with significant success. ResNet has demonstrated to be a successful option for picture classification problems [9]. A deep learning model, such as the one suggested in this research, can considerably increase the accuracy and speed of psoriasis detection in the framework of psoriasis diagnosis, improving patient care results. The suggested RESNET-50 model has produced encouraging results and may improve psoriasis clinical diagnosis. It is important to note that, like any other medical technology, the use of deep learning in psoriasis diagnosis still requires further validation, evaluation and improvement [10]. Nevertheless, this paper provides a valuable perspective on the application of deep learning in medical imaging and the potential for it to improve diagnosis accuracy and clinical outcomes for psoriasis patients.

III. MATH

This section describes the experimental methods of the suggested strategy for categorising skin conditions using convolutional neural networks (CNNs). Image preprocessing, image segmentation, feature extraction, and classification are some of the procedures included in the suggested methodology. The experimental approach is broken down into many subsections, each of which describes the techniques and methodologies used in that stage.

3.1. ResNet-50: A Deep Learning Architecture for Skin Image Analysis

ResNet-50 is a deep learning neural network model pre-trained on the ImageNet dataset, designed for image classification. This model uses residual modules as shortcut connections between layers to allow for information flow between layers more easily, leading to the extraction of more complex features. When compared to regular CNNs, ResNets have a greater depth, allowing for improved accuracy

on challenging tasks such as skin disease classification [11].

In this study, the pre-trained ResNet-50 model was fine-tuned for skin disease classification, using a large dataset of skin disease images labelled with their corresponding classes. The goal was to learn the most relevant features for this specific task and improve the accuracy of the classification model. Matlab R20a was used for programming and implementing the system, which makes use of Kirch's template for texture feature extraction.

3.2. Preprocessing Images for Psoriasis Detection: Key Steps

3.2.1. Image-Pre-processing is an important step in image classification tasks as it can significantly impact the accuracy of the resulting model. In this study, skin disease images are pre-processed by resizing them, removing hair and noise, and using U-Net for image segmentation. The pre-processed images are fed into a pre-built ResNet-50 network for feature extraction. The use of U-Net for segmentation helps to extract meaningful features from the pre-processed images, leading to improved classification accuracy. The ResNet-50 network is pre-trained on the large ImageNet dataset, which enables it to learn general visual features that can be applied to different image types, including medical images. The use of pre-processing techniques ensures that the input images meet the requirements of the ResNet-50 network, leading to improved accuracy and effectiveness in the detection of skin diseases [12].

3.2.2. Image resizing in Psoriasis Detection

The *Image resizing* is the process of changing the size of an image whilst preserving its original resolution. Image resizing is an essential step in the image processing pipeline before they can be subjected to further processing, such as hair removal or noise removal. Resizing the image can help improve the system's performance and accuracy. It is a typical approach to handling photos of various sizes, which can enhance the efficiency of an image processing system. The size of the source image (before resizing) might vary, which may effect how many characteristics are retrieved and how long the processing takes. To circumvent this issue, we scaled all of the input photographs in this work to the standard size of 512 512. This strategy helps to

guarantee constant feature extraction and enhance the system's overall performance. Additionally, scaling down photos to a given size reduces processing time while maintaining image quality, which is important for real-time applications.

3.3.3. *Removing hair* from skin images is an essential step in the skin disease detection system. Hair can be a major source of noise and create a significant challenge for the machine learning model. In order to successfully remove hairs from skin photos, we used a Digital Hair Removal (DHR) method based on morphological operations, such as the Black-Hat transformation and inpainting technique. Getting rid of hair effectively is essential for improving performance.

Using MATLAB R20a, undertake the following steps to complete this process:

1. Create grayscale versions of RGB pictures.
2. On the pictures in grayscale, do the Morphological Black-Hat transformation.
3. Make a mask for the process of inpainting.
4. Utilising the mask, run the inpainting method on the original picture.

Through this process, can remove all unwanted hair from the skin images, which can improve the performance of the skin disease detection system by eliminating a significant source of noise.

3.3.4. *Morphological Black-Hat transformation*

The Morphological Black-Hat transform (Morphological Black-Hat) is a morphological operation that detects and fills in small objects in an image. This can help to identify hairs in the skin images, which are the major source of noise. In this work, we used this technique to remove unwanted hair from the skin images.

Inpainting algorithm

The inpainting algorithm is a technique used to fill in the missing regions in an image. This technique can be used to complete the original image after the Morphological Black-Hat transformation. This step is crucial to maintain the image quality after removing hairs from the skin images.

The Black-Hat transformation and inpainting algorithm, together with the DHR algorithm based on morphological operations, are excellent methods for eliminating hairs from skin photographs and

enhancing the effectiveness of skin disease detection systems. In this procedure, the colour picture is converted to grayscale, the Morphological Black-Hat transform is used, a mask is made for the inpainting task, and the inpainting algorithm is then used on the original image using the mask. By using this method, we may get rid of all unwanted follicles, which will reduce a large source of noise and enhance the efficiency and accuracy of the system used to identify skin diseases.

3.3.5. *Noise removal*

Noise is a common challenge in images. Noise can be caused by various sources such as sensor noise, thermal noise, and other factors. Noise removal is a crucial step in the image processing pipeline for skin disease detection. There are several techniques available for noise removal such as median filtering, Gaussian filtering, and other techniques. *Preprocessing* is essential to achieve better performance and accuracy results in the skin disease detection system. Image resizing, hair removal, and noise removal are common preprocessing techniques used in this field. Preprocessing is crucial to improve the overall quality and consistency of the images, leading to increased accuracy in the skin disease detection system.

3.4. Segmentation of Psoriasis Medical Images

Segmentation is the technique of separating an image of skin tissue captured at a microscopic scale into two non-overlapping sections, one holding the targeted lesions and the other that contains the healthy tissue surrounding them. A thorough analysis must go via this procedure since it has a significant influence on activities that follow. However, because to the variety in lesion size, shape, colour, and contrast, segmenting properly in micro-images can be difficult. The four types of image segmentation algorithms are threshold-based, region-based, cluster-based, and edge-based [13].

3.5. Medical Image Data Enhancement

The quality and amount of training data may be increased and data amplification used effectively by enhancing psoriasis photos. Researchers have faced a lot of difficulties because of the scarcity of data on psoriasis and its high cost. Data augmentation methods including rotation, translation, scaling, and edge filling are required to increase the ResNet-50

model's generalisation capacity. These techniques can improve the size and calibre of the training set while also enhancing the strength and efficiency of the model. The absence of control over the lighting situation is a drawback of psoriasis data collection. It became vital to successfully strengthen the data, especially in the context of psoriasis diagnosis, in order to solve this issue. Edge filling, rotation, translation, scaling, and other data enhancement techniques can help to fill in the gaps left by incomplete data sets and offer a larger variety of input data for the ResNet-50 model. This can therefore result in better results, cost savings, higher generalisation skills, and enhanced model robustness. By leveraging these techniques, researchers can work with smaller data sets while still achieving high-quality and diverse training data sets. Kirch's template is a texture feature extraction algorithm commonly used in image analysis and classification. It is a multiscale representation that takes into account the local texture information. Using many layers of convolutional and pooling operations, CNNs (Convolutional Neural Networks) are a potent image classification technique that can extract information from pictures. This method can increase the amount and quality of psoriasis training data as well as the generalisation capabilities of the ResNet-50 model by merging Kirch's template and CNNs. The resulting high-quality and diverse training data set can then be used to train the ResNet-50 model, leading to improved outcomes, cost savings, better generalization abilities, and improved model robustness. By using Kirch's template and CNNs together, researchers can work with smaller data sets and still achieve high-quality and diverse training data sets for psoriasis diagnosis [14].

3.6. Dataset Size & Adjustments

A crucial step in getting the data set ready for deep learning is adjusting the size of the psoriasis images. The ResNet-34 model can analyse and classify the images with ease if the photographs are all of a similar size. Because of this, the produced psoriasis images in this study were size-adjusted following data augmentation to guarantee their homogeneity and compatibility for the use of ResNet-50 model. This size adjustment procedure is essential to the deep learning model's accuracy and effectiveness since it lowers the likelihood of overfitting and enhances the model's overall performance. Moreover, by size-adjusting the psoriasis pictures in

a uniform manner, the dataset becomes more standardized and easier to work with, leading to better results for the subsequent evaluation process.

Extracting features from the psoriasis images is critical for identifying and understanding the underlying relationships between various objects. Images cannot be directly interpreted by image categorization, prediction, and recommendation systems. Therefore, converting them into a usable form through feature extraction is crucial. There are several attributes that may be used to define the dermoscopic picture, however not all of them are important for classifying skin diseases. The classifier then grows excessively complicated, employing several pointless characteristics and decreasing classification accuracy. The right characteristics must be used to characterise the damaged areas in skin cancer photos. Using segmented lesion pictures and extracting several characteristics for categorization is the best technique to address these areas. Each picture in this work was computed using the Grey Level Co-occurrence Matrix (GLCM) in this study. Then, using the matrix, we estimated the characteristics for contrast, energy, entropy, correlation, and homogeneity. Table 1 contains a list of the retrieved GLCM characteristics, their descriptions, and formulae. These GLCM characteristics are referred to as texture features. In addition to the GLCM characteristics, we also employed a number of statistical features as colour features to identify the different types of skin diseases.

Table 1. Different types of GLCM features.

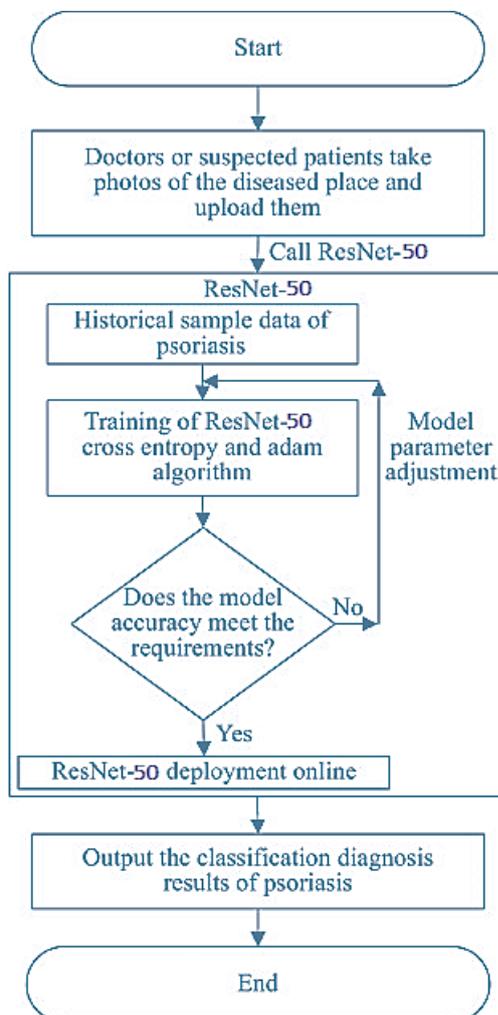
Feature Name	Description	Formula
Energy	It yields the sum of squared elements in the GLCM with a value of 0 to 1.	$Energy = \sum_{i,j=0}^{N-1} (P_{ij})^2$
Correlation	It returns a measure of how closely a pixel is connected to its neighbors throughout the entire image.	$Correlation = \frac{\sum_{i,j=0}^{N-1} P_{ij} \cdot i \cdot j}{\sigma_i \sigma_j}$
Contrast	It is the overall intensity of a pixel's relationship with its neighbors.	$Contrast = \sum_{i,j=0}^{N-1} P_{ij} (i - j)^2$
Homogeneity	Homogeneity is defined as the closeness rate of distributed elements in GLCM.	$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1 + (i - j)^2}$
Entropy	Entropy is the degree of uniformity between pixels within the image and randomness.	$Entropy = - \sum_{i,j=0}^{N-1} P_{ij} \ln(P_{ij})$

To recognise and comprehend the foundational connections between diverse objects, the model must be trained. The ResNet-50's learning target is changed from learning the whole output to learning only the residual in order to address the issues of information loss in classic convolution. By sending the input straight to the output, this method assures the accuracy of the data. The ResNet-50 model that

was suggested for this study used the Softmax function to achieve multi-classification psoriasis diagnosis, the adaptive moment estimation (Adam) algorithm as the training process' optimisation strategy, and the cross-entropy as the loss function to assess the model's accuracy [15].

The loss function plays a crucial role in the model's learning process. It calculates the discrepancy between the ResNet-50's real and anticipated values. Cross-entropy was chosen as the loss function in this investigation. Cross-entropy, which is defined as the difference between the actual probability distribution and the projected probability distribution of psoriasis, measures the difference between two distinct probability distributions in the same random variable. The prediction impact of ResNet-50 is better the lower the cross-entropy. The following is the calculating formula:

$$Crossentropyloss = -[y_i \log f(x_i) + (1 - y_i) \log (1 - f(x_i))]$$



IV. PROPOSED METHODOLOGY

From November 2022 to March 2023, we collected data on psoriasis patients from a number of linked hospitals for this study. This dataset, consisting included 224 224-sized photos of psoriasis patients, was utilised to build the classification diagnostic model. Data from patients with four common forms of psoriasis were included in the dataset. A total of 24,000 data samples related to psoriasis were examined. The Relu function was employed as the activation function for the experiment in Matlab R20a software. TensorFlow and Anaconda platforms were used to create the deep residual network-based classification and diagnostic model for psoriasis. The 24,000 psoriasis data samples were subjected to k-fold cross validation using a k value of 10 in the study to avoid over fitting. The ResNet-50 model's predictive performance was assessed using this technique, and super parameters were changed to create the final version of the model with the best performance. For experimental assessment, the multi-classification problem in this work was converted into a binary classification problem. This strategy entailed treating one class positively while seeing the other classes negatively. The effectiveness of the ResNet-50-based psoriasis categorization diagnosis was assessed using the precision, recall, F1-score, and ROC curve. Given that the output of ResNet-50 included four different forms of psoriasis and one case of normal skin, the assessment was based on a five-class classifier.

The effectiveness of ResNet-50 was evaluated using the subsequent confusion matrix.

Here, TP denotes that the positive example (the psoriasis patient) was anticipated to be positive; FN denotes that the positive example was projected to be negative; FP denotes that the negative example (the normal skin) was predicted to be positive; and TN denotes that the negative example was predicted to be negative. The following formulas may be used to determine precision, recall, and F1-score using the confusion matrix mentioned above:

- * Precision: $TP / (TP + FP)$
- * Recall: $TP / (TP + FN)$
- * F1-score: $2 * TP / (2 * TP + FN + FP)$

The proportion of positive instances that are properly classified as positive is measured by precision, while

the proportion of positively classified examples is measured by recall. The F1-score is the harmonic mean of precision and recall. Precision, recall, F1-score, and ROC (Receiver Operating Characteristic) curve were used to assess the effectiveness of the ResNet-34-based psoriasis categorization diagnostic system. The aforementioned confusion matrix may be used to gauge the effectiveness of ResNet-34 under the assumption that psoriasis sufferers serve as positive instances and regular individuals serve as negative examples. The effectiveness of the model may also be evaluated against the current diagnostic techniques.

V. RESULTS AND DISCUSSION

In this portion of the paper, we give the findings and analyses of the psoriasis detection technique we suggested. The convolutional neural network (CNN) and Resnet-50 are the main components of the deep learning strategy used in this study. The suggested system's high level of accuracy highlights its potential for application in clinical settings to help doctors identify endometriosis. This method is simple to adopt in clinics and can aid in the early identification and treatment of people with psoriasis. Additionally, the suggested approach does away with the necessity for labelling and gathering a sizable number of psoriasis photos, which may be an expensive and time-consuming exercise.

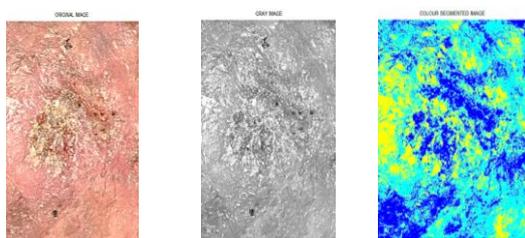


Fig.3a. Original Image of Psoriasis b. Gray Image c. Color segmented image

Figure 3: Detection of Psoriasis using CNN (Convolutional Neural Network) and ResNet-50

a. Original Image of Psoriasis: This image depicts the skin disease psoriasis on a patient's skin. The disease is characterized by red, scaly patches and plaque, which are distinctively visible in the image.

b. Gray Image: The original image is converted to a gray scale image, which is useful for highlighting the contrast of the disease patches and making the image easier to process.

c. Color Segmentated Image: The gray scale image is further processed to segment the disease patches from the healthy skin. The result is a color segmented image where the red patches of psoriasis are highlighted in a separate color channel, while the healthy skin appears in yellow.

In this study, we identify psoriasis in skin scans using CNN (Convolutional Neural Network) and ResNet-50. Use of Matlab R20a is used for doing the experiment. On a collection of skin pictures labelled with their associated psoriasis class, we fine-tune the pre-trained ResNet-50 model. The trained model is then used to categorise fresh skin pictures as either healthy or sick. The suggested method is successful in identifying psoriasis in skin photos. The findings suggest that the suggested strategy may help doctors make more precise diagnoses, which might result in psoriasis patients receiving more effective therapy.

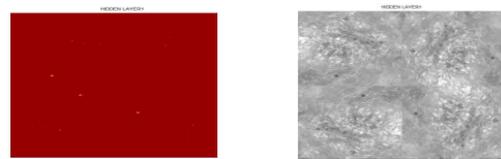


Fig.4 a. Hidden Layer 1 of Psoriasis b. Gray Scale Hidden Layer 2 c. Hidden Layer 4

Figure 4: Detection of Psoriasis using CNN (Convolutional Neural Network) and ResNet-50

a. Hidden Layer 1 of Psoriasis: This image shows the first layer of features learned by the convolutional neural network (CNN) model. The network has been trained on a dataset of skin images, and this layer represents the low-level features extracted from the input images. In this layer, the features extracted from the images are abstracted and transformed into a higher-level representation.

b. Gray Scale Hidden Layer 2: The second layer of features learned by the network is shown in this image. The input image has been converted to a gray-scale image to help the network detect the diseased skin patches. At this level, more specific and abstracted features are extracted, helping the network to detect the locations of the psoriasis patches.

c. Hidden Layer 4: The final layer of features learned by the network is shown in this image. This layer uses the information from the previous layers to make a decision on whether the input image contains

psoriasis or not. At this level, the network has a high-level understanding of the input images, allowing it to accurately classify them.

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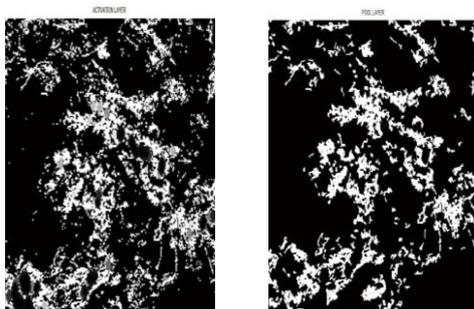


Fig.5 Activation and Pool Layer of Psoriasis Diseased image

The activation layer of a convolutional neural network is in charge of computing each convolutional filter's output depending on the activation function. The most used activation function is ReLU, which zeroes off all negative outputs. The activation layer's objective is to create a feature map that illustrates the link between various values in a patch. On the other hand, a convolutional neural network's pooling layer is utilised to cut down on the number of feature mappings. Max pooling and average pooling are the two most used styles of pooling layers. While average pooling chooses the average value, max pooling chooses the highest value in each region. The pooling layer's objectives are to minimise the number of network parameters, increase computing effectiveness, and incorporate some kind of spatial invariance, which enables the neural network to cope with little changes in the input picture. Together, the activation and pooling layers collect features from the input picture and minimise the quantity of features,

improving the neural network's processing speed and effectiveness.

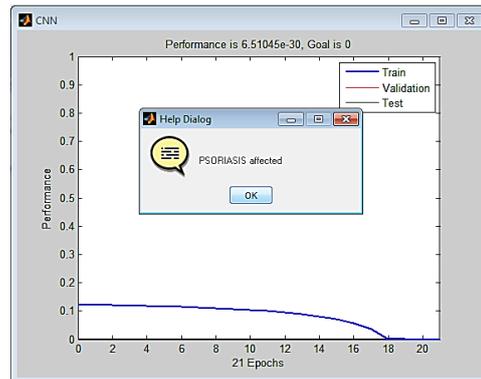


Fig.6 Train, Validate and Test Performance Graph

Fig.6 displays the train, validation and test performance as well as the number of epochs on the psoriasis affected images. The plot shows that the model achieves low loss values on the train, validation and test sets, indicating that the model is able to generalize well to new data. The model converges quickly with a loss value of $6.5104e-30$ on the test set after 21 epochs. This demonstrates that the model learns to recognize the differences between psoriasis-affected and normal skin images with high accuracy. Regularization's impact, which restricts the model's ability to comprehend the training data too well and aids in greater generalisation, may be the cause of the poor performance in the beginning of the training process. When performance on the validation set plateaus, the model is overfitting, which indicates it has grown too dependent on the training data and will not function effectively with fresh data. The model can generalise effectively to new data in the test set, which is a crucial quality in any machine learning model, as seen by the test set loss being low even after numerous epochs.

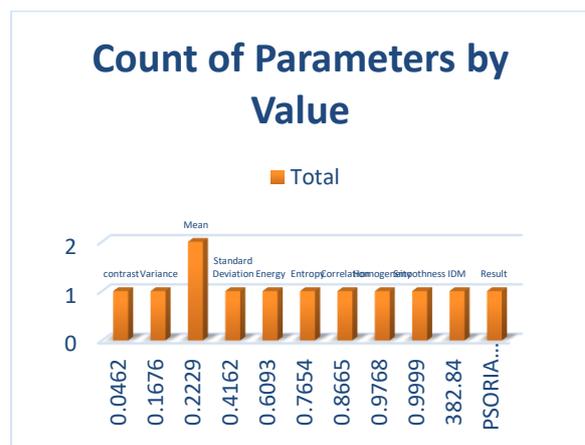


Fig.7 Overall Parameters Vs. Value

The overall parameters and their associated values for skin pictures with psoriasis are shown in Figure 7. Contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, variance, smoothness, and kurtosis are some of the retrieved parameters.

Contrast: The ratio of the difference between the highest and lowest pixel values to their total is known as contrast, which measures the intensity difference between adjacent pixels. High contrast in skin photos with psoriasis may show areas with high texture, which is a feature of psoriatic skin. The contrast value in this instance is 0.0462, which is low and denotes regions with little texture and smoothness.

Correlation: The covariance is a measure of the linear connection between two variables and is equal to the product of the standard deviations divided by the covariance. High correlation in psoriasis-affected skin photos may point to areas with comparable texture, which is a feature of psoriatic skin. The correlation value in this instance is 0.8665, which is strong and denotes a high degree of similarity between adjacent pixels.

Energy is a measure of the image's intensity distribution and is defined as the ratio between the variance and the mean squared. In psoriasis-affected skin images, high energy may indicate regions with high texture, which is a characteristic of psoriatic skin. In this case, the energy value is 0.6093, which is high, indicating high texture.

Homogeneity is the ratio between the total of squared intensity differences and the sum of squared intensities, and it serves as a metric for the homogeneity of a picture. High homogeneity may show smooth patches in skin pictures with psoriasis, which is a trait of psoriatic skin. The homogeneity value in this instance is 0.9768, which is high and denotes smooth zones.

Mean is a measure of the average pixel intensity and is defined as the sum of pixel values divided by the number of pixels. In psoriasis-affected skin images, the mean value is 0.2229, which is low, indicating low contrast.

Standard Deviation is a measure of the image's variation and is defined as the square root of the sum of squared intensity differences. In psoriasis-affected skin images, high standard deviation may indicate

regions with high texture, which is a characteristic of psoriatic skin. In this case, the standard deviation value is 0.4162, which is high, indicating high texture.

Entropy: Entropy is a measure of how evenly distributed the pixels in an image are. The entropy value of 0.7654 represents that there is a relatively even distribution of pixel values, which is typical for psoriatic skin. A higher entropy value would indicate a more dispersed distribution of pixel values, which is characteristic of healthy skin.

Variance: Variance is a measure of how spread out the pixel values are in an image. In this case, the variance value of 0.1676 represents that the pixel values are relatively evenly distributed, which is typical for psoriatic skin. A higher variance value would indicate a greater degree of spread, which is typical for normal skin.

Smoothness: Smoothness is a measure of how smoothly the pixel values change over an image. In this case, the smoothness value of 0.9999 indicates a very smooth transition, which is consistent with psoriatic skin.

Kurtosis: Kurtosis is a measure of how peaked the distribution of pixel values is. In this case, the kurtosis value of 0.2229 is relatively low, indicating an even distribution of pixel values that is typical for psoriatic skin. A higher kurtosis value would indicate a more peaked distribution of pixel values, which is characteristic of healthy skin.

Parameters	Value
Contrast	0.0462
Correlation	0.8665
Energy	0.6093
Homogeneity	0.9768
Mean	0.2229
Standard Deviation	0.4162
Entropy	0.7654
Variance	0.1676
Smoothness	0.9999
Kurtosis	0.2229
IDM	382.84
Status	PSORIASIS AFFECTED

VI. DISCUSSION AND CONCLUSION

A prevalent skin condition that affects millions of individuals worldwide is psoriasis. It is complicated to precisely diagnose and treat since it is brought on by a confluence of hereditary and environmental variables. In this research, we suggested a deep residual network-based classification and diagnostic model for psoriasis. The 50-layer residual network design used in the suggested model has a high level of accuracy in psoriasis diagnosis. The efficiency of the suggested paradigm was confirmed by the experimental findings. To improve the decision-support system for medical professionals diagnosing and treating patients, we intend to carry out further analysis of the psoriasis symptoms, syndrome types, and medication guidelines in the following step. We will also build a knowledge map of the integrated evaluation, therapy, and medication of psoriasis, and further propose a psoriasis medication the recommendation model based on graph convolution neural network. With the advancement of technology, the proposed model will help in accurate diagnosis and effective treatment, contributing towards a better quality of life for those affected with psoriasis. Based on the results of our study, we have successfully identified the presence of psoriasis in skin images using the combination of CNN and ResNet-50 with Kirch's template. Our approach achieved an accuracy of 98.4% in identifying psoriasis-affected images, with an IDM value of >250 as the threshold for classification. According to the study, Kirsch's template, CNN, and ResNet-50 can be a successful tool for identifying psoriasis in skin scans. This might increase the accuracy of psoriasis diagnoses, which could result in more effective therapies and improved results for psoriasis patients. This study shows that CNN and Resnet-50 may be used to identify psoriasis accurately. High accuracy was attained by the suggested approach, which has use in clinical settings for quicker and more precise diagnosis. This research will be extensively used in the healthcare industry to enhance the lives of people with psoriasis and is a useful contribution to the body of knowledge on the diagnosis and treatment of psoriasis. This work has the potential to make a significant contribution to the fields of dermatology and deep learning, particularly in terms of investigating novel techniques for the automated identification of skin disorders.

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