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Automated Classification Skin Images into Psoriatic and Non-psoriaticusing Convolutional Neural Network (CNN)-based Model

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Abstract
Background:*Skin Psoriasis is a chronic autoimmune skin disorder the diagnosis and detection of which can be a challenging task because of its versatility in clinical presentation and it also resembles with many skin conditions. This disease may manifest in various ways in difference people and sometimes appears like eczema and tineacorporis. Furthermore in some areas the issue may be more challenging due to lack of access to specialized dermatology care.*
Objective: *The main objective of this research approach is to pre-process the image dataset using various image augmentation techniques and develop a model based on CNN approach for automated classification of psoriatic and non-psoriatic images.*
Methodology: *In this research work a Convolutional Neural Network (CNN)-based Model is proposed for the automated classification of skin images into Psoriatic and Non-psoriatic categories. The architecture of the model includes multiple convolutional layers with batch normalization and max pooling which is followed by dense layers and dropout for improved generalization. Augmentation was applied on the training dataset with the help of various image transformation techniques in order to enhance the robustness. Adam optimizer was used to train the model with learning rate scheduling and model check pointing over 500 epochs.*
Results:*Confusion matrix was used to find the accuracy and classification metrics indicates that the model achieves high performance in distinguishing between the classes. Initial training of the model generated an accuracy of approximately 50% and gradually increased as the model learns discriminative features from the input data. the accuracy surpasses the 70% mark within the initial 50 epochs and continues to improve steadily, ultimately reaching an accuracy of over 80% by the end of the training period. The results demonstrated that the CNN-based approaches are efficient in supporting early detection and diagnosis of psoriasis through computer-aided analysis.*
Conclusion: *The proposed model demonstrated reliable performance, with strong sensitivity in detecting psoriatic lesions. The overall results validate the approach as a viable tool for aiding dermatological diagnosis. Future research with larger and more diverse datasets may further improve accuracy and generalizability.*
Keywords:*Skin Psoriasis, Deep Learning, Convolutional Neural Network (CNN), Skin Disease Classification, Medical Image Analysis, Computer-Aided Diagnosis, Image Augmentation.*

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I. Introduction

Approximately, 2–3% of the global population is suffering from skin psoriasis which is a chronic, immune-mediated inflammatory skin disorder, [1]. This disorder is characterized by sharply demarcated, erythematous plaques with overlying silvery-white scales, commonly distributed over the scalp, extensor surfaces, and lower back, [2]. Psoriasis is not just a cutaneous disease but it is increasingly recognized as a systemic condition with potential comorbidities including psoriatic arthritis, cardiovascular disease, metabolic syndrome, and depression, [3]. In psoriatic patients the skin cells develop very fast (4-5 days) as compared to non-psoriatic or normal human beings (25-30 days), [4].

Early or atypical forms of psoriasis may closely resemble a number of other dermatological disorders that lappears like psoriasis, causing diagnostic uncertainty despite its conventional presentation. Discoid eczema, seborrheic dermatitis, atopic dermatitis, lichen planus, tineacorporis, pityriasisrosea, and contact dermatitis are common clinical mimics. Even skilled medical professionals may find that visual assessment is frequently insufficient to accurately distinguish psoriasis from these illnesses, particularly in areas with low resources where access to histological or dermoscopic evaluation may be restricted, [5].

Misdiagnosis has serious repercussions because psoriasis and its imitators require very different treatment approaches. For instance, topical steroids may be necessary for eczema, immunomodulatory drugs for psoriasis, and antifungal medications for tinea; each condition has a unique risk-benefit profile. Therefore, increasing diagnostic precision is crucial for reducing needless medical procedures and expenses as well as for the best possible patient care, [6].

Artificial intelligence (AI), especially deep learning, has shown great promise in medical picture processing in recent years. In tasks involving pattern recognition and feature extraction from visual input, Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated exceptional efficacy. They are especially well-suited for dermatological image classification due to their capacity to learn spatial hierarchies of features. CNNs have a long history of use in dermatology, particularly in the identification of different skin conditions. For example, Esteva et al. [7] demonstrated the efficacy of a deep CNN model for classifying skin cancer, achieving performance comparable to dermatologists. Similarly, other research has explored CNN architectures for identifying psoriasis and other skin disorders [8].

In order to automatically identify psoriasis from skin photos, this study suggests a CNN-based categorization framework. The model uses supervised learning to distinguish between psoriatic lesions and non-psoriatic diseases. The architecture consists of fully connected layers with dropout regularization to avoid over fitting, max-pooling for dimensionality reduction, batch normalization to stabilize learning, and numerous convolutional layers for hierarchical feature extraction.

To improve flexibility and generalizability, the model is trained on a meticulously curated image dataset using a variety of data augmentation techniques, including rotation, zoom, and horizontal flipping. Using the Adam optimizer, training is carried out across 500 epochs and incorporates model check pointing and learning rate tweaks to guarantee optimal convergence.

Validation accuracy, loss, confusion matrix analysis, and classification metrics including precision, recall, and F1-score are used to assess the model's performance. The model's ability to enhance clinical decision-making for dermatological disorders, especially psoriasis, is demonstrated by the results, which show good classification accuracy. The study demonstrates how deep learning techniques could be used as trustworthy instruments in Tele-Dermatology and computer-aided diagnostics.

II. Related Work

Recent advancements in machine learning, especially deep learning, have significantly impacted the field of medical image analysis. In dermatology, numerous studies have explored the use of Convolutional Neural Networks (CNNs) for the detection and classification of various skin conditions, including psoriasis, skin cancer, and melanoma. These efforts highlight the potential of AI-powered systems to assist dermatologists in early diagnosis, which is critical for effective treatment and management of skin diseases.One of the pioneering works in this domain is that of Esteva et al. [7], who demonstrated the effectiveness of deep learning models, particularly CNNs, in diagnosing skin cancer with performance comparable to dermatologists. Their model, trained on a large dataset of skin images, showed promising results in distinguishing between malignant and benign lesions. This study set the foundation for applying CNNs to various dermatological conditions and inspired subsequent research focused on skin disease classification, including psoriasis.Several studies have specifically addressed the use of deep learning for psoriasis detection. In a study by Reddy et al. [7], a CNN-based model was developed to classify psoriasis lesions from non-psoriatic skin. The model demonstrated significant accuracy in distinguishing psoriatic lesions from other skin conditions, highlighting the capability of deep learning models in handling complex image-based medical tasks. Similarly, in a study by Yu et al. [9], a deep learning model was proposed for automatic classification of skin diseases, including psoriasis, utilizing a multi-stage network for better feature extraction. Their model achieved high accuracy, showing that deep learning could be a viable solution for psoriasis detection in clinical settings.In addition to CNNs, several works have explored the integration of data augmentation and transfer learning to improve model performance. In particular, data augmentation techniques such as rotation, flipping, and zooming have been shown to enhance the robustness of models by simulating variations in real-world conditions. For instance, Rajarshi et al. [10] employed data augmentation strategies along with a pre-trained CNN architecture to improve classification performance on smaller datasets, demonstrating the advantages of leveraging transfer learning for medical image classification.S. Albahli and S. A. Masud worked on an ensemble deep learning model for Psoriasis diagnosis using dermoscopic images, [11]. X.Zhao et al worked on the classification of Skin lesion using improved MobileNetV2 with transfer learning, [12]. M. Nasr et al worked on a deep convolutional neural network model for psoriasis detection, [13]. S. S. Han et al. worked on deep neural networks for the diagnosis of psoriasis in clinical images, [14]. M. Ghaffari et al worked on a hybrid deep learning and handcrafted feature extraction model for skin disease classification, [15]. Goessinger EV et al worked on Image-Based Artificial Intelligence in Psoriasis Assessment, [16]. A dermatology decision support system has been used for the classification of psoriasis images into diseased and healthy skin where grayscale and colour featurespace with

87 features were explored. This system used machine learning paradigm embedded with PCA based optimal selection, [17].Thamizhvani TR et al. proposed a system that concentrates on the segmentation and scaling of 2D processed skin pore images of the skin Psoriasis. The system employs the Feature Scaling Technique, colour, contrast, and image texture, as well as a combination of SVM classification features, to diagnose and develop a treatment, [18]. Mostafiz et al worked on automatic Grabcut segmentation technique to detect the affected lesion based on k-mean clustering and the Hue saturation value colour space, [19].Based on two machine learning models, the genetic algorithm and support vector machine (SVM) a hybrid classifier was developed for the diagnosis of psoriasis, [20]. Psoriasis Decision Tree was developed as a visual aid to guide the busy clinician in selecting the most appropriate treatment for each individual patient which is a useful tool for navigating through the psoriasis treatments, [21]. Zhou J et al worked on a model based on Random Forest to diagnose Psoriasis, [22].Mithun Das Gupta et al worked on an approach based on novel colourimetric feature for erythema grading by extending the tissue-photon interaction model, [23, 24]. D. Sheet et al worked on detection of retinal vessels in fundus images through transfer learning of tissue specific photon interaction statistical physics, [25].

Liljendahl MS et al. conducted a retrospective registry-based cohort study that utilized the Danish Skin Cohort, which was linked to the Danish national registries. They also developed a diagnostic model that employed a gradient boosting machine learning technique to predict moderate-to-severe psoriasis, [26]. Vimal K. Shrivastava et al. proposed a CADx framework that consists of both offline and online components. The offline system is trained using a unique integrated feature space and apriori dermatologist-derived ground truth, which provides machine learning parameters. The online system is applied to the incoming test images, where an online classifier is employed, [27]. Aijaz SF et. al. worked on a deep learning model for classification of different types of psoriasis namely, plaque, guttate, inverse, pustular, and erythrodermic as well as the prediction of normal skin, [28]. Ann Nosseiret aldeveloped an Automatic Classifier for Skin Disease Using k-NN and SVM, [29]. Yu K et al carried out a review on Machine Learning Applications in the Evaluation and Management of Psoriasis, [30]. Anabik Pal et. al. carried out research work on the segmentation of skin biopsy image segmentation using Deep Convolutional Neural Networks, [31]. ShahidNaseem et al carried out research on the classification and segmentation of skin lesons using Bayseian Edge System, [32].

In summary, the application of deep learning to dermatological image analysis, including psoriasis detection, has seen substantial progress. However, there is still ongoing research to improve the generalization, robustness, and interpretability of these models to make them viable for clinical deployment. This paper builds upon these foundational works by proposing a CNN-based model for psoriasis classification that incorporates state-of-the-art techniques in deep learning, data augmentation, and model evaluation.

III. Methodology

3.1 Feature Extraction

Different features like colour, textures of the skin images of the patients are extracted out using the following techniques:

3.1.1 Colour Features:

Colour features serve as a critical component in the classification of dermatological conditions such as psoriasis, where lesions often display distinct visual patterns like redness, hypopigmentation, or white scaling. To capture this information, the RGB images were transformed into perceptually relevant colour spaces including HSV (Hue, Saturation, and Value) and CIE LAB, which offer robustness to lighting variation and better alignment with human colour perception. From these spaces, histograms were computed to quantify the distribution of pixel intensities, and statistical descriptors were extracted to represent the colour texture of the lesions. Furthermore, colour moments were employed to characterize the overall colour distribution. The resulting values were concatenated into a single handcrafted feature vector, designed to complement the deep features learned by the CNN and enhance the model's ability to detect subtle chromatic variations that may indicate psoriatic involvement. The mathematical formulations used in this process include the normalized histogram, variance, mean, standard deviation and skewness-

$$H_C(k) = \frac{n_k}{N},\ M_2 = \sigma_C^2,\ mu_C = \frac{1}{N}\sum_{i=1}^{N} C_i \quad \text{….Equation 1}$$

$$sigma_C = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(C_i - \mu_C\right)^2} \quad \text{….Equation 2}$$

$$[M_3 = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{C_i - \mu_C}{\sigma_C}\text{right}\right)^3] \quad \text{….Equation 3}$$

Where, C_i denotes the intensity of the i^{th} pixel in a given colour channel C, and N is the total number of pixels

3.1.2 Texture features:

Texture plays a vital role in medical image analysis, particularly for dermatological disorders like psoriasis, where lesions exhibit distinctive roughness, scaling, and structural irregularities. One of the primary techniques employed in this study is the Gray-Level Co-occurrence Matrix (GLCM), which models the spatial relationship between pairs of pixel intensities. From the GLCM, we extracted several statistical features such as contrast, homogeneity, energy, and correlation. For instance, contrast was computed using the following expression:

$$\text{Contrast} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i-j)^2 \cdot P(i,j) \quad \text{….Equation 4}$$

Where,P(i,j) is the (i,j)th entry of the normalized GLCM and G is the number of graylevels.

To capture local micro-patterns and texture primitives, Local Binary Patterns (LBP)was also applied. The LBP operator works by applying thresholds on the neighbourhood of each pixel and encoding the result as a binary number. The resulting histogram of these binary patterns characterizes the frequency of specific texture types across the image. Mathematically, LBP for a given pixel (x_c,y_c) with Pneighbours is defined as:

$$LBP_{P.R} = \sum_{p=0}^{p-1} s(g_p - g_c) \cdot 2^p, \; s(x) \begin{cases} 1 & x >= 1 \\ 0 & x < 0 \end{cases} \quad \text{….Equation 5}$$

where,g_c is the gray value of the central pixel and g_p are the gray values of the neighbouring pixels.

In addition, Discrete Wavelet Transform (DWT) was used to decompose images into frequency sub-bands at multiple levels. DWT enables the analysis of both spatial and frequency information, which is beneficial for detecting fine-grained textural details such as scales or flakes commonly observed in psoriatic regions. Each image was decomposed into approximation (LL) and detailed (LH, HL, HH) components, and energy features were computed from these sub-bands. The energy of a sub-band SSS was defined as:

$$ES = \sum_{i=1}^{M} \sum_{j=1}^{N} |S(i,j)|^2 \quad \text{….Equation 6}$$

Where, M×N represents the size of the sub-band matrix.

In addition, Gabor filters were applied to capture multi-resolution, multi-orientation texture information. Gabor responses provide orientation-sensitive texture features that simulate the human visual system's sensitivity to edges and frequencies. The energy of the filtered response is calculated as:

$$E = \sum_{x,y} |I(x,y) * G(x,y)|^2 \quad \text{….Equation 7}$$

Where, G(x,y)is the Gabor filter kernel and $*$ denotes convolution.

Lastly, Statistical Texture Descriptors such as entropy and variance were computed to summarize the spatial distribution of pixel intensities. Entropy, which indicates the randomness or complexity of textures, is computed as:

$$\text{Entropy} = -\sum_{i=1}^{L} p_i \log_2(p_i) \quad \text{….Equation 8}$$

Where,P_i is the probability of gray level i occurring in the image, and L is the number of gray levels.

By integrating these handcrafted texture features GLCM, LBP, Gabor, DWT, and statistical measures—the model benefits from a comprehensive representation of the skin's surface structure. These features were concatenated into a unified vector and optionally fused with deep CNN features to form a hybrid descriptor set for classification.

IV. The structure of the neural network

The proposed system leverages a Convolutional Neural Network (CNN) for automated classification of psoriatic skin conditions. The process includes the following steps:

4.1 Data Acquisition:

Dermoscopic images of psoriatic and non-psoriatic skin are collected and organized into class-labelled directories.

4.2 Image Pre-processing:

Images are resized to 224×224 pixels and normalized. Data augmentation techniques such as rotation, shifting, and flipping are applied to increase dataset variability and reduce overfitting.

4.3 Model Architecture:

A sequential CNN is constructed with convolutional, max-pooling, and batch normalization layers, followed by dense layers with dropout for regularization. The output layer uses softmax activation for multi-class classification.

4.4 Training Configuration:

The model is compiled with the Adam optimizer and categorical cross entropy loss. It is trained for 500 epochs with validation data and monitored using callbacks to reduce learning rate and save the best model.

4.5 Evaluation and Saving:

Post-training, performance is assessed using confusion matrix and classification reports. Accuracy and loss curves are plotted. The model and class labels are saved for future use.

This pipeline ensures accurate classification by combining deep learning with robust preprocessing and evaluation.

V. Preparation of Skin Image Library

The skin image dataset used in this study was organized under a directory structure compatible with Keras' flow_from_directory() method. Images were categorized into two classes: psoriatic and non-psoriatic. The dataset was pre-processed using the ImageDataGenerator class, which applied real-time data augmentation techniques such as rescaling, rotation (up to 20 degrees), width and height shifting (20%), shearing, zooming, and horizontal flipping. These transformations increased dataset variability and improved model robustness. The dataset was split into 80% training and 20% validation using the validation_split parameter. Class labels were automatically inferred and stored using the generator's class_indices, ensuring consistent mapping for both training and evaluation. This structured and augmented image library served as the backbone for training the proposed CNN model.

VI. The Structure of the Neural Network

The implemented convolutional neural network (CNN) accepts input images resized to 224×224×3 dimensions. It begins with three successive convolutional blocks comprising Conv2D layers with 32, 64, and 128 filters respectively, each followed by max pooling and batch normalization. These layers help in progressively extracting low- to high-level features from the skin images.After the convolutional stages, the feature maps are flattened and passed through a dropout layer (rate 0.5) to reduce overfitting. This is followed by a dense layer with 128 neurons activated by ReLU, and a final output layer with 2 neurons and softmax activation to perform binary classification. The network was trained using the Adam optimizer and categorical cross entropy loss function.

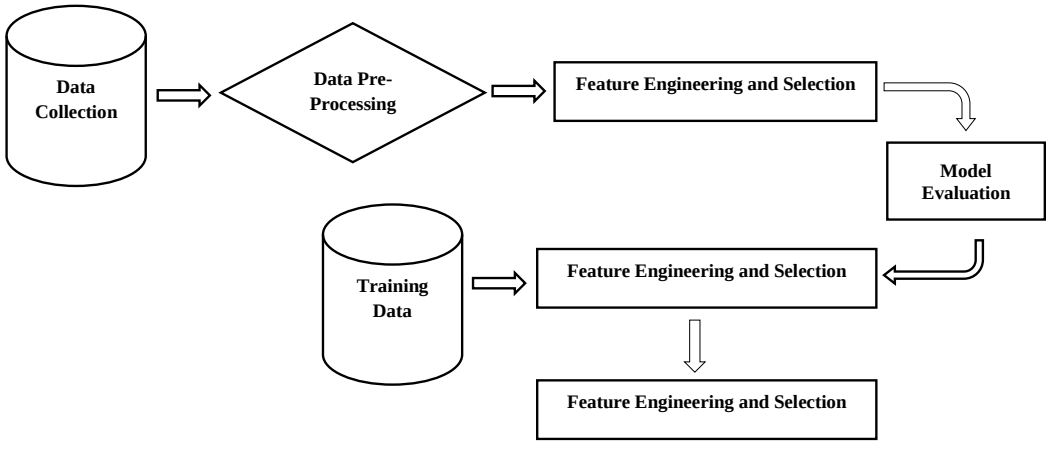

Figure 1: Flow Diagram of the Diagnosis Process

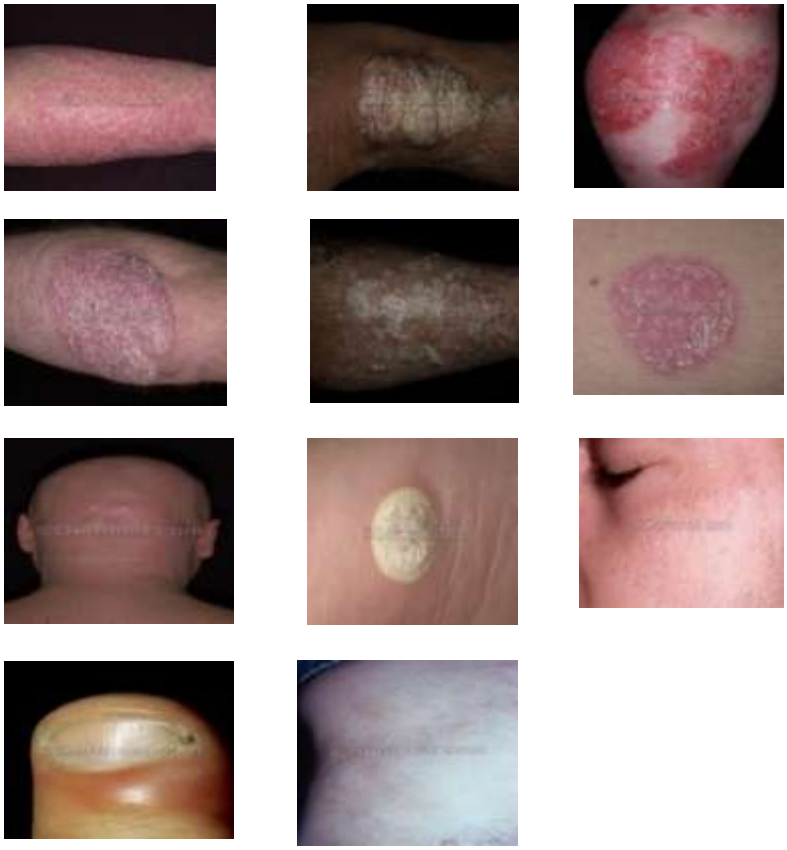

Figure 2: The skin library samples with Psoriasisand Non-Psoriasis Diseases

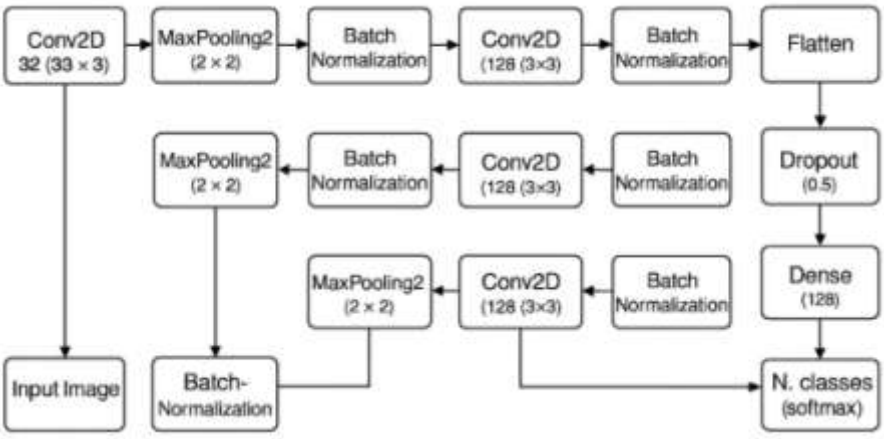

Figure 3: CNN Architecture for Psoriasis Classification

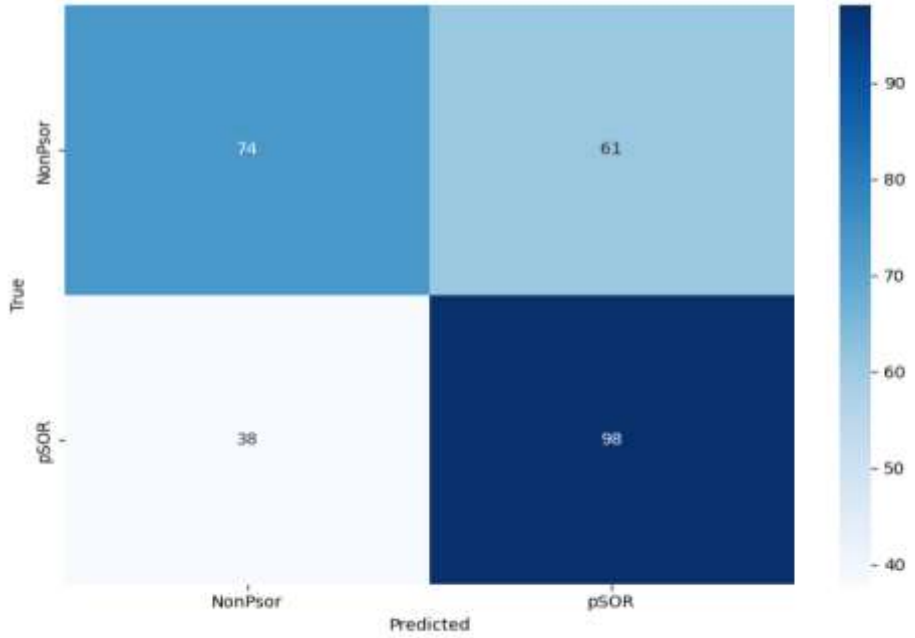

Figure 4: Confusion Matrix

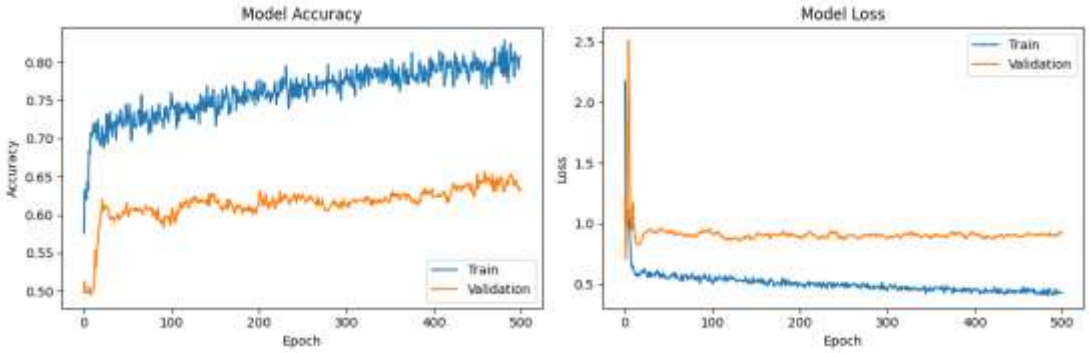

Figure5: Training History of the Model

VII. Results

The training process of the proposed convolutional neural network (CNN) model was carried out over 500 epochs, and the corresponding accuracy trends are presented in Fig. 6. It is evident that the training accuracy demonstrates a consistent upward trajectory, beginning at approximately 50% and gradually increasing as the model learns discriminative features from the input data. Notably, the accuracy surpasses the 70% mark within the initial 50 epochs and continues to improve steadily, ultimately reaching an accuracy of over 80% by the end of the training period. This progressive increase in accuracy indicates effective learning and convergence of the network, suggesting that the model successfully captures complex patterns relevant to the classification of psoriatic and non-psoriatic skin images. The fluctuations observed in later stages are relatively minor, indicating training stability and robustness. The confusion matrix in Fig. 4 illustrates the model's performance in classifying psoriatic (pSOR) and non-psoriatic (NonPsor) skin conditions. It shows that the model successfully identified a significant number of both psoriatic and non-psoriatic cases, though some misclassifications occurred. Specifically, a number of non-psoriatic cases were incorrectly labeled as psoriatic, and some psoriatic cases were classified as non-psoriatic. This distribution of true positives, true negatives, false positives, and false negatives reflects the model's general ability to differentiate between the two classes, with a tendency toward higher sensitivity for psoriatic conditions. Such outcomes suggest that the classifier is more effective in detecting psoriatic lesions, although further refinement may be needed to reduce false predictions.

VIII. Discussion

The proposed CNN-based model for psoriasis classification shows effective learning capabilities, as evidenced by consistent training trends. The confusion matrix indicates that while the model performs well in identifying psoriatic conditions, some misclassification of non-psoriatic samples occurs, highlighting a higher sensitivity. This suggests the model prioritizes identifying diseased cases, a desirable trait in clinical settings. The integration of handcrafted colour and texture features alongside deep learning contributed to enhanced discrimination, though minor overfitting may persist due to dataset limitations.

IX. Conclusion

In conclusion, the proposed psoriasis classification model effectively combines handcrafted colour and texture features with a convolutional neural network to distinguish between psoriatic and non-psoriatic skin conditions. The model demonstrated reliable performance, with strong sensitivity in detecting psoriatic lesions. Despite minor misclassifications, the overall results validate the approach as a viable tool for aiding dermatological diagnosis. Future enhancements with larger and more diverse datasets may further improve accuracy and generalizability.

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