



A Comparative Study of CNN, Vision Transformer, and Hybrid Architectures for Psoriasis Image Classification

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Abstract. Psoriasis is an inflammatory skin disease which considerably impacts the quality of life, and thus the necessity to involve clinical experts for its correct diagnosis. Due to the resemblance of psoriasis with other similar dermatologic diseases and the unavailability of dermatologists in various geographical locations, there is a need to automate the diagnostic process with the help of AI technologies. The current paper explores an approach to computer-aided psoriasis assessment based on an empirical comparison between different CNN, ViT, and a novel EfficientNetB4-Transformer-based framework. Specifically, a combined dataset comprising 3,755 dermoscopic and clinical images was built from publicly available psoriasis databases, where 2,351 images belong to psoriasis cases, and 1,404 to non-psoriasis cases. The dataset was preprocessed in terms of resizing, normalization, and image augmentation to enhance the models' robustness. The hybrid architecture proposed consists of EfficientNetB4 and the use of transformer-based attention mechanisms. The suggested hybrid deep learning framework yielded better performance metrics in terms of 98.27% accuracy, 99.58% precision, 97.73% recall, 98.64% F1-score, and 0.9998 ROC-AUC score. The study findings indicate the benefits associated with using convolutional and transformer neural networks for increasing discriminative ability and improve classification accuracy in the case of skin images affected by psoriasis. The proposed framework is intended to function as a decision-support tool for AI-assisted psoriasis screening rather than a replacement for expert dermatological diagnosis.

Keywords: Psoriasis Classification, Deep Learning, EfficientNetB4, Vision Transformer, Hybrid Architecture, Medical Image Analysis

1 Introduction

Psoriasis is an inflammatory condition of the skin that arises due to autoimmune activity in which there is excessive proliferation of cells of skin, leading to the appearance of reddish and scaly lesions on the skin surface [1], [3]. The disease has affected millions of people globally and considerably influences their physical and mental health. Apart from the skin lesions, psoriasis is known to cause many other health

problems like psoriatic arthritis, cardiovascular diseases, and psychological distress, highlighting the need for timely detection and monitoring [3]. However, the difficulty of diagnosing psoriasis lies in the visual similarity of the disease with various skin ailments such as eczema, dermatitis, and fungal infections. Diagnosis through traditional methods has depended on the skills of dermatologists in recognizing skin lesions visually [1], [2].

Recent progress in the field of AI and Deep Learning (DL) has greatly enhanced the ability to support clinical screening in medical image analysis through effective feature extraction and precise image classification [2], [5]. Early machine learning methods used to detect psoriasis lesions were based on designing features manually, along with the application of classifiers like Support Vector Machines (SVM) and Random Forests [4]. While the performance of these models was moderate, it was highly dependent on manual feature designing and image quality.

Another major milestone in dermatology was contributed by Deep Convolutional Neural Networks (CNN), which had the potential to learn hierarchical representations from raw images [10], [11], [12]. Deep CNN models have proven to be capable of detecting lesion specific features including scales, erythemas, and texture abnormalities. Conventional CNN models mainly focus on capturing information within local receptive fields and might lack the ability to understand contextual relationships among skin lesions. To overcome this drawback, vision transformers, which use the self-attention mechanism to learn global interactions among regions within an image, can be used [8], [9]. Despite being good at modeling long-range dependencies within image data, transformers often require large quantity of data and computation power.

In view of the advantages of both CNNs and transformer models, the present paper suggests an innovative architecture combining EfficientNetB4 and Transformer to facilitate automatic psoriasis classification. The suggested approach involves incorporating EfficientNetB4 as a means of extracting local features together with utilizing transformers for self-attention in order to capture global context. The comparison between the suggested model, Custom CNN, EfficientNetB4, and Vision Transformer was conducted based on the combined dataset including 3,755 images depicting both psoriasis and non-psoriasis cases.

2 Literature Review

Accurate diagnosis of skin disorders like Psoriasis is usually challenging due to the visual resemblance to various other skin disorders, such as eczema and dermatitis [1], [2], [3]. The existing traditional diagnosis approach mainly relies on expert knowledge and observation from dermatologists; therefore, it is subject to subjective observer variation and diagnosis delays in areas where medical facilities are lacking. It is these limitations that drive researchers to explore artificial intelligence and deep learning techniques in automatic psoriasis diagnosis.

Earlier studies in automatic skin disease detection made use of the conventional Machine Learning (ML) paradigm in conjunction with manual feature engineering. Hameed et al. [4] proposed a system for skin lesion detection based on hand-crafted

features and traditional ML models. Despite the moderate effectiveness of such approaches, their success heavily depended on the chosen feature extraction methodology and image quality. Likewise, other machine learning systems utilizing Support Vector Machine and Random Forest classifiers proved to be insufficiently flexible when dealing with clinically heterogeneous images [1].

The creation of deep convolutional neural networks (CNN) greatly advanced the medical image classification process through the ability to extract hierarchical features from raw image data automatically. In their study, Zhao et al. [10] proposed a psoriasis detection system based on deep CNN architectures with clinical skin images showing high diagnostic efficacy for lesions. Additionally, Wu et al. [11] introduced a DL algorithm for inflammatory skin disease diagnosis with efficient architectures called EfficientNet, providing a higher classification accuracy while being computationally efficient. Likewise, Yang et al. [12] showed that psoriasis images from a dermoscopy could be used to train CNN models that could match dermatologists' diagnostic accuracy.

Even though CNNs are good at extracting features locally within the skin lesion images, they usually fail to understand long-distance spatial associations within them. To solve this problem, transformer-based approaches have recently been developed in computer vision specifically in medical imaging. Dosovitskiy et al. [9] designed the ViT architecture that employs self-attention algorithms to learn contextual dependencies globally in an image. Later, Mashal et al. [8] extended this idea to propose a ViT-based approach for classifying psoriasis images and showed better results than some well-known CNN-based classifiers. Although transformer approaches show better context understanding, they need more data and higher computation costs.

The latest research has considered artificial intelligence applications for the quantification of psoriasis severity and explaining the dermatological analysis process. For example, Carthy et al. [5] applied artificial intelligence approaches to PASI score prediction, which reflects the increasing importance of artificial intelligence in the quantification of diseases. The utilization of the neural networks approach to nail psoriasis prediction was analyzed by Ricardo et al. [6], and the authors obtained a good correlation between predictions made with AI and evaluation by dermatologists. In addition, Folle et al. [13] offered DeepNAPSI - deep learning-based nail psoriasis prediction method.

Though both CNNs and Vision transformers can be individually used for attaining good classification results, there are certain limitations associated with them. The shortcomings of CNN lies in its ability to capture fine-grained texture information locally while it may not be able to learn global context dependency, on the other hand, transformer architecture is good at learning global representation; however, it needs significant training data and computation capacity [8], [9]. Therefore, recently much attention has been devoted to using the combination of CNN and Transformer architecture, which includes the strengths of both methods.

In light of such progressions, the current study suggests a novel hybrid network architecture that consists of the combination of EfficientNetB4 and Transformer models to classify psoriasis images. The suggested architecture incorporates a combination of local feature extraction using EfficientNetB4 along with self-attention using trans-

formers for capturing global context information. Apart from the evaluation of the suggested hybrid approach, comparisons have been carried out using Custom CNN, EfficientNetB4, and Vision Transformer architectures.

Table 1. Comparative Analysis of Existing Psoriasis Classification Approaches

Study	Architecture	Contribution	Accuracy
[10]	CNN	Automated psoriasis classification	96%
[11]	EfficientNet	Skin disease diagnosis	95.8%
[8]	Vision Transformer	Transformer-based psoriasis classification	97.53%
[7]	Hybrid CNN	Hybrid psoriasis classifier	89.73%
Proposed Method	EfficientNetB4 + Transformer	Local-global feature fusion	98.27%

3 Methodology

The methodology was developed to create an effective and reliable hybrid deep learning architecture for psoriasis image classification using both feature extraction through convolutions and contextual information learned via transformers. For training the neural network, the dataset was assembled by merging two publicly available Kaggle datasets on psoriasis [14], [15]. Visually identical or near-identical images were manually excluded to ensure uniqueness. Images were organized into two categories based on their class labels: Psoriasis and Non-Psoriasis. After data preprocessing and merging, there were 3,755 total images in the dataset, 2,351 being psoriasis images, and 1,404 non-psoriasis images. To make classification more difficult and improve the effectiveness of the proposed system, the non-psoriasis class includes not only images of healthy skin but also skin lesions that look like psoriasis in appearance. Medical image databases usually include diverse examples of various illumination and lesion orientations, quality of images, and skin type, so various steps of preprocessing were implemented to the database.

Every image was downsized into a uniform resolution of 224×224 pixels to assure compatibility with all architectures tested in this experiment. Normalization of the pixels was performed based on the standard parameters of ImageNet. To increase the variability within the dataset and mimic realistic image capturing conditions, augmentation through random rotations, flips, changes in brightness levels, zooming in/out, and addition of noise were employed during training. Stratified validation holdout technique was implemented to maintain the integrity of the original class distribution between the training and validation datasets. The `image_dataset_from_directory` function from TensorFlow library was utilized with a fixed validation split of 0.2 and random seed to achieve around 80% training samples consisting of 3,004 images and 20% validation samples containing 750 images. This way, no data leakage occurred due to the complete isolation of validation images during training. All experiments were conducted on the Kaggle cloud platform using TensorFlow and Keras with GPU

support. A batch size of 16 with 20 epochs was set during training, while Adam optimization and binary cross-entropy loss functions were selected.

For the assessment of the efficacy of the proposed architecture, comparative analysis was conducted using three different models: Custom CNN, EfficientNetB4, and Vision Transformer (ViT). The Custom CNN model was considered for inclusion to show a typical convoluted model, whereas EfficientNetB4 was considered due to its good compromise between efficacy and computational requirements. Vision Transformer was chosen in order to assess the impact of attention-based global contextual learning on the psoriasis images. To incorporate the local texture description and global spatial correlation modeling, a hybrid architecture of EfficientNetB4-Transformer was also designed.

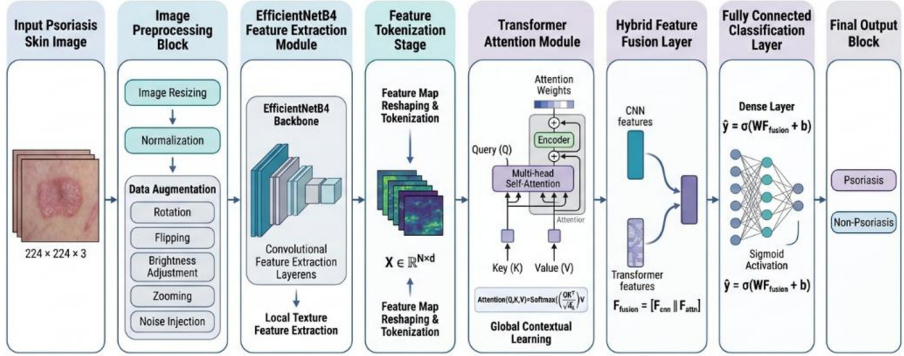


Fig. 1. Proposed Hybrid EfficientNetB4–Transformer Architecture for Psoriasis Classification

Initially, the input image ($I \in \mathbb{R}^{224 \times 224 \times 3}$) is processed through the EfficientNetB4 feature extractor to generate high-level convolutional representations. This operation can be expressed as:

$$F_{cnn} = \phi_{cnn}(I) \quad (1)$$

where (F_{cnn}) represents the feature representation extracted from the EfficientNetB4 backbone and (ϕ_{cnn}) denotes the convolutional feature extraction process. These features represent unique information related to scaling, erythema, and boundary irregularities. The generated feature maps are further transformed into tokens before being fed into the attention module of transformers. We assume that the tokenized feature representation is represented as $X \in \mathbb{R}^{N \times d}$ where N represents the number of tokens and d is the dimension of the embedding. The Query, Key, and Value matrices are defined as $Q = XW_Q$, $K = XW_K$, $V = XW_V$. The transformer layer employs scaled dot product self-attention to capture long-range dependencies in the lesion images:

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (2)$$

where (Q), (K), and (V) depicts the query, key, and value matrices derived from the input features, while (d_k) represents the dimensionality of the key vectors used for scaling. This attention mechanism facilitates the dynamic allocation of importance to various parts of the tumor image. This provides for more than what can be captured using the convolutional receptive fields of the network. This contextual feature vector is computed as follows:

$$F_{attn} = \phi_{attn}(F_{cnn}) \quad (3)$$

where(F_{attn}) denotes the transformer-generated contextual feature representation. In the hybrid model, the combination of local convolution features and global contextual features using transformers occurs via feature concatenation. Here F_{cnn} represents the flattened feature representation from the EfficientNetB4 architecture, whereas F_{attn} corresponds to the transformer attention output. The concatenation process can be formally defined as follows:

$$F_{fusion} = \alpha \cdot F_{cnn} + \beta \cdot F_{attn} \quad (4)$$

where (α) and (β) are learnable weighting coefficients and (F_{fusion}) represents the final fused feature representation. The fused representation is subsequently passed through fully connected layers followed by sigmoid activation for binary classification:

$$\hat{y} = \sigma(W \cdot F_{fusion} + b) \quad (5)$$

where (W) and (b) denote trainable parameters, (σ) represents the sigmoid activation function, and ($\hat{y}$) corresponds to the predicted probability score. If images had probabilities larger than 0.5, they would be considered psoriasis images, whereas other samples were considered to be non-psoriasis images.

In order to make sure that our experimental evaluation will be reliable and there is no chance of having any data leakage, we have kept strict stratification throughout our experiment in the validation process. In other words, the proportionate distribution of psoriasis and non-psoriasis samples will be maintained in training and validation both sets. However, the validation set will remain unseen while optimizing the model parameters. The model has been trained for 20 epochs with batch size 16, and evaluation has been done only on the validation set. The stable convergence achieved between the training and validation accuracy graph, as well as gradual decrease of validation loss graph, proves better generalization without overfitting.

4 Results and Discussion

This study was conducted to analyze the efficiency of the proposed hybrid EfficientNetB4–Transformer model compared to the baseline models, which include Custom CNN, EfficientNetB4, and Vision Transformer (ViT). The models were trained with similar data preprocessing techniques, data augmentation techniques, image resolution, batch sizes, and validation processes to make a reasonable comparison. Efficient-

cy was the model assessed using accuracy, precision, recall, F1-score, and ROC-AUC measures.

The comparative efficiency findings are summarized in Table 2. The Custom CNN model exhibited the poorest performance since it had limited capability in extracting features from complex lesions in heterogeneous skin images. The EfficientNetB4 model showed substantial improvements owing to its improved capability for feature extraction and efficient scaling process. The ViT model offered better performance than the previous models by utilizing self-attention mechanisms to model long-term contextual dependencies. Nonetheless, the proposed hybrid EfficientNetB4–Transformer model provided superior performance through the integration of local texture representation and global context learning.

The accuracy, precision, recall, F1 score, and ROC-AUC scores of the suggested hybrid model were 98.27%, 99.58%, 97.73%, 98.64%, and 0.9996, respectively, with the model outperforming all baseline models on all other measures except one. The high precision shows the model’s capability to avoid making false positives, while high recall shows the ability to effectively detect the presence of psoriasis cases.

Table 2. Comparative Performance Analysis of Deep Learning Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Custom CNN	88.42	87.65	86.91	87.28	0.921
EfficientNetB4	95.84	96.12	94.76	95.43	0.982
Vision Transformer (ViT)	96.73	97.21	95.88	96.54	0.989
Proposed Hybrid Model	98.27	99.58	97.73	98.64	0.9998

The convergence of the designed algorithm was also examined through the use of training and validation curves. As depicted in Figure 2, there is stable convergence of training and validation accuracy, showing that the developed algorithm can effectively generalize data without much overfitting. Validation losses also steadily declined throughout training epochs, reflecting better feature generalization of the model.

Through confusion matrix analysis, it shows that the performance is relatively balanced with only 13 instances of incorrect predictions out of 750 validation samples. Based on the confusion matrix results, it can be stated that there is a balance in terms of predictions for both classes, that is, psoriasis and non-psoriasis, as well as low false negatives and false positives. Also, from the training and validation accuracies' proximity to each other, we can conclude that there was no significant divergence while training during subsequent epochs. Through ROC analysis, the high-class separability of the model was proven by the proximity of the curve to the upper left region and obtaining an ROC–AUC score of 0.9996.

The higher efficiency of the proposed hybrid model is due to the synergy between EfficientNetB4 feature extraction and context learning using transformers. The EfficientNetB4 model efficiently captured lesion-specific texture features, whereas the attention-based mechanism within the transformer architecture learned long-distance spatial correlations in the lesion image. The combination of local and global features

contributed to robust detection irrespective of different imaging scenarios such as variable illumination and lesion orientation.

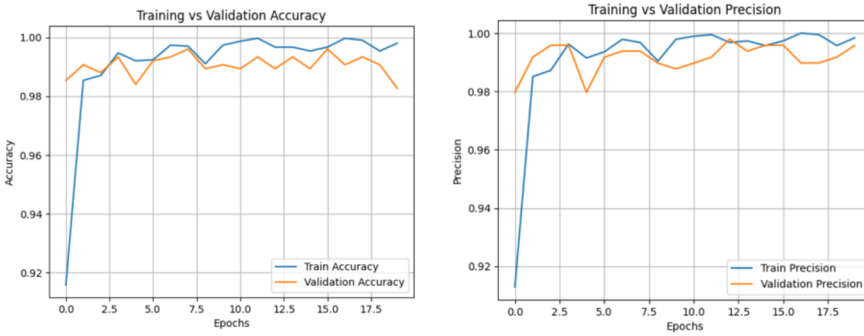


Fig. 2. Training and Validation Accuracy and loss Curves of the Hybrid Model

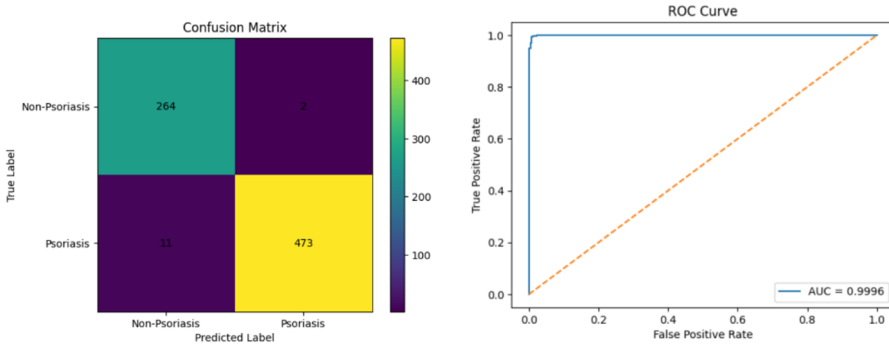


Fig. 3. Confusion Matrix and ROC curve of the Hybrid EfficientNetB4–Transformer Model

5 Conclusion and Future works

In this research, a comparative and detailed study was performed for the evaluation of various DL architectures to demonstrate potential applicability in psoriasis image classification with respect to convolutional, transformer-based, and hybrid learning techniques. The integration of the convolutional learning approach and transformer model into a hybrid EfficientNetB4-Transformer framework was proposed to utilize the advantages of convolutional feature extraction and transformer-based contextual modeling for the problem at hand. The efficacy of the proposed model framework was evaluated using a combination of different baseline models such as Custom CNN, EfficientNetB4, and Vision Transformer (ViT), which were tested on the combined psoriasis and non-psoriasis image dataset containing 3,755 images derived from publicly available dermatological datasets. Experimentally derived results showed that the proposed hybrid framework outperformed other models in terms of image classification accuracy with metrics of 98.27% accuracy, 99.58% precision, 97.73% recall, 98.64% F1-score, and ROC-AUC of 0.9998. These results show that the combination

of local texture representation with global contextual modeling can be very useful in improving discriminative performance during medical image classification problems.

The combination of fusion methods adopted was able to capitalize on the advantages inherent in both approaches and successfully performed classification in the presence of heterogeneous imaging conditions, which included variations in lighting conditions, lesion orientation, skin texture, and image quality. Further, the analysis of convergence, confusion matrix, and ROC curve indicated enhanced generalization performance with decreased chances of overfitting and data leakage. Even though the suggested model was able to show good results in terms of classification, the model is expected to be used only as an assisting tool in AI-based psoriasis detection, and not to replace human diagnosis by any means. Nonetheless, there were some drawbacks associated with the approach adopted. For instance, the dataset used in this research is based on publicly available data sets. Additionally, the present system classifies images using binary classification and cannot identify different types of psoriasis or the level of their severity. The lack of validation of this system using any external clinical data makes its practical use difficult. In future work, one can consider validating this system using more clinical data involving varied skin tones. One can also include explainable AI methods like Grad-CAM to help in further understanding. Furthermore, the system can be expanded into a multi-class classification for different dermatological diseases along with severity analysis.

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