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Optimized Deep Neural Network for High-Precision Psoriasis Classification from Dermoscopic Images

Red neuronal profunda optimizada para la clasificación de psoriasis de alta precisión a partir de imágenes dermatoscópicas

Bolia, Charu [1*]
Joshi, Sunil[1]

[1]Department of Electronics and Communication Engineering, CTAE, MPUAT, Udaipur, India 313001

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Corresponding author*: charu.bolia@gmail.com
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ABSTRACT

Accurate classification of psoriasis is critical in dermatological diagnostics due to the disease's diverse clinical presentations and varying severity levels. With numerous subtypes and their visual similarities to other dermatological conditions, precise diagnosis typically requires expert medical knowledge. Early and accurate identification of psoriasis subtypes is essential for initiating timely treatment. This study introduces a novel hybrid deep learning architecture that integrates EfficientNet with Long Short-Term Memory (LSTM) networks for the automated classification of psoriasis from dermoscopic images. The proposed model is designed to simultaneously capture spatial features through EfficientNet and temporal or sequential patterns via LSTM units, thereby improving classification performance. The models are trained and tested on a publicly benchmark dataset comprising 7 distinct classes using the publically available benchmark dataset by Dermnet and BFL-NTU. Experimental results demonstrate that the proposed architecture significantly outperforms the baseline models such as VGG16 and ResNet50, with superior accuracy 89.7% and robust performance across metrics like recall, F1-score with 88%, and Region of Convergence (ROC) of 97%. This compact design with low trainable parameters reduces the computational time and memory makes the model well-suited for deployment for portable devices and enabling real-time mobile-based dermatological assessments.

Keywords: skin disease; long short term memory; psoriasis; efficient net

RESUMEN

La clasificación precisa de la psoriasis es crucial en el diagnóstico dermatológico debido a las diversas presentaciones clínicas de la enfermedad y sus distintos niveles de gravedad. Con numerosos subtipos y sus similitudes visuales con otras afecciones dermatológicas, un diagnóstico preciso generalmente requiere conocimientos médicos especializados. La identificación temprana y precisa de los subtipos de psoriasis es esencial para iniciar un tratamiento oportuno. Este estudio presenta una novedosa arquitectura híbrida de aprendizaje profundo que integra EfficientNet con redes de memoria a largo plazo (LSTM) para la clasificación automatizada de la psoriasis a partir de imágenes dermatoscópicas. El modelo propuesto está diseñado para capturar simultáneamente características espaciales mediante EfficientNet y patrones temporales o secuenciales mediante unidades LSTM, mejorando así el rendimiento de la clasificación. Los modelos se entrenan y prueban en un conjunto de datos de referencia público que comprende siete clases distintas, utilizando el conjunto de datos de referencia disponible públicamente de Dermnet y BFL-NTU. Los resultados experimentales demuestran que la arquitectura propuesta supera significativamente a los modelos de referencia, como VGG16 y ResNet50, con una precisión superior del 89,7% y un rendimiento robusto en métricas como la recuperación, la puntuación F1 del 88% y la región de convergencia (ROC) del 97%. Este diseño compacto, con bajos parámetros de entrenamiento, reduce el tiempo de cálculo y la memoria, lo que lo hace ideal para su implementación en dispositivos portátiles y permite evaluaciones dermatológicas móviles en tiempo real.

Palabras clave: enfermedad de la piel; memoria a corto plazo; psoriasis; red eficiente

1. INTRODUCTION

It is a well-known fact that psoriasis is a long-lasting, inflammatory, and autoimmune disease of the skin that targets people all over the world, becoming unbearable for the affected ones. The disease is excessively characterized by the rapid growth of skin cells, which, in turn, leads to skin thickening and the formation of scales, reflecting a local reaction of the body (Adegun & Viriri, 2020; Lowes et al., 2007; Pham et al., 2020; Wijesinghe et al., 2019). This type of psoriasis is usually covered with silvery white scales and red, and its appearance causes the feeling of itching, irritation, and pain.There are a few kinds of psoriasis, including plaque (the most common variation), guttate, Inverse, pustular, and erythrodermic psoriasis (Hammad et al., 2023). Every form is characterized by totally different symptoms, and as a result, accurate diagnosis and classification are essential parts of the treatment process and the management of the disease (Griffiths & Barker, 2007). That is why building up automatic and smart diagnostic systems is so important in the process of supporting and enhancing the skills of dermatologists involved in the diagnosis, enabling them to carry out their job much faster and more accurately at the same time.

Machine Learning (ML) has become one of the most innovative technologies in healthcare, with medical image classification and disease diagnosis being the areas of the most significant impact (Esteva et al., 2017). Deep Learning (DL), a subset of Machine Learning (ML), has significantly transformed image-based diagnosis by enabling automatic feature extraction directly from raw data, eliminating the need for manual feature engineering. Convolutional Neural Networks (CNNs) are among the most widely used techniques for image classification, primarily due to their hierarchical architecture, which effectively captures spatial and contextual information (Aishwarya et al., 2020; Ayad & Ismail, 2020; Huang et al., 2020). One of the most pertinent benefits of Deep Learning is its capability to manage these enormous and complicated datasets, which in turn increases the accuracy of classifying the data, and all of this is done with neither manual feature engineering nor the necessity to have the right dataset and the right features (Krizhevsky et al., 2017).

Transfer learning has come up as a remedy to handle the lack of data in the area of medical image processing (Bolia & Joshi, 2024). This method entails the use of pre-trained models that are initially created using extensive datasets like Image Net and adjusting them to suit the precise needs of the target domain. This transfer learning approach shortens training duration and improves model performance, especially in the context of limited or small datasets (LeCun et al., 2015).

Although numerous researchers have worked on classifying skin diseases, only a handful has focused on types of psoriasis. Ahmmed et al. (2025) proposed a modified VGG-16-based approach for distinguishing between psoriasis and actinic keratosis, achieving approximately 90% classification accuracy. While the method demonstrates strong performance in binary classification tasks, it does not address the differentiation between various subtypes of psoriasis, limiting its applicability in more granular diagnostic scenarios (Ahmmed et al., 2025).

A total of 263 samples were analysed, such as 143 from psoriasis patients and 120 from healthy individuals. Six machine learning models were applied, with the Extra Trees Classifier achieving the highest accuracy of 96.1%. The findings highlighted the potential of breath analysis for early detection of psoriasis. J. Wang, et al. (2025) presented a multimodal framework which was trained on the PUMCH-ISD dataset covering eight inflammatory skin conditions (Wang et al., 2025).

V. Jagannathan, et al. (2024) presented a hybrid deep learning model that combined CNN (Convolutional Neural Networks) with Bi-GRU (Bidirectional Gated Recurrent Units) to improve dermatological image classification. The model achieved high accuracy 0.818 for multi-class and 0.911 for binary classification surpassing both single-modality and basic fusion models. It also outperformed 11 advanced methods on the Derm7 dataset with an accuracy of 0.807. Furthermore, it improved diagnostic accuracy for dermatologists with 79.1% of cases showing improved performance. (Jagannathan et al., 2024).

The research conducted in 2023 by Singh.et al. introduces a deep learning framework for detecting psoriasis through transfer learning with VGG-16, VGG-19, and Inception V3. The models were assessed using a labeled image dataset of psoriasis conditions. Of the three, Inception V3 attained the highest accuracy of 91%. The article highlights how well deep CNNs can identify skin conditions and advocates for the use of pre-trained models for dependable classification. (Singh et al., 2023).

Azam et al. (2022) applied machine learning algorithms including SVM, Naïve Bayes, KNN, and Decision Tree to classify psoriasis using microarray gene expression data. Their findings showed that SVM, combined with effective feature selection, achieved the highest accuracy, demonstrating strong potential for genomic-based psoriasis diagnosis (Azam et al., 2022).

Deep learning techniques utilized by S.F. Aijaz et al. (2022) to categorise various forms of psoriasis. The researchers used databases covering five different forms of psoriasis from BFL NTU and Dermnet. They used a Convolutional Neural Network (CNN) model, which has an accuracy of 84.2% and analyses images pixel by pixel. They also investigated a Long Short-Term Memory (LSTM) technique, which uses historical inputs to analyse sequential data, although this method only achieved 72.3% accuracy (Aijaz et al., 2022).

A deep residual network-based model for classifying psoriasis was presented by Li Peng et al. in 2021. Their model seeks to improve accuracy, expedite the diagnostic process, and reduce the workload of medical practitioners by utilising deep learning technologies (Peng et al., 2021). They started by pre-processing the incoming data with methods like image resizing and data augmentation. They then built ResNet-34 to extract the distinctive characteristics of psoriasis from the input pictures.

Previous research has primarily focused on distinguishing skin cancer and psoriasis from healthy skin or a limited range of other skin conditions. However, the classification of psoriasis subtypes has received relatively little attention. Moreover, while models such as modified VGG16 and Res Net have been commonly employed, EfficientNet architectures have also demonstrated promising performance in multiclass classification tasks (Bolia & Joshi, 2024). EfficientNet models achieve state-of-the-art accuracy while maintaining significantly fewer parameters and lower computational complexity (FLOPs) compared to traditional convolutional neural networks. EfficientNet contains approximately 5.3 million parameters, which is considerably less than ResNet50 with 25.6 million and VGG16 with 138 million parameters. Despite this compact architecture, EfficientNet not only matches but often surpasses the performance of deeper and more complex models such as ResNet152, making it an effective and resource-efficient choice for image classification tasks. Also, Long Short-Term Memory (LSTM) have shown its efficacy in earlier cited work (Aijaz et al., 2022; Azam et al., 2022; Jagannathan et al., 2024; Singh et al., 2023). This paper outlines an integrated deep learning model that merges EfficientNet with a powerful CNN architecture - Bidirectional Long Short-Term Memory (LSTM) network to classify psoriasis diseases.

The main contribution of this paper is:

(1) The proposed model integrates EfficientNetB3 for spatial feature extraction with an LSTM network, which models dependencies across sequentially ordered feature vectors derived from the image. Although the input is a static image, representing spatial features as sequences allows the LSTM to capture contextual relationships across regions, thereby improving the classification of psoriasis subtypes.

(2) The psoriasis classes Plaque, pustular, inversus, erythrodermic, guttate types of psoriasis along with psoriasis on scalp and nails are taken into attention.

(3) The proposed model offers a novel configuration characterized by low inference time and a reduced number of trainable parameters, making it well-suited for deployment with mobile and portable devices.

2. MATERIALS AND METHODS

2.1. Experimental Set up Database collection

Research has been conducted to classify different forms of Psoriasis skin disease. It was implemented in Python using Keras with tensor flow and the open CV library with 32GB RAM and a Card (GPU) Intel(R) UHD Graphics 770 (NVIDIA T600) 4G, 12th Gen.Intel (R) core (TM) i5-12600K, 3.70GHz CPU, at the Department of Computer Science Engineering, CTAE, MPUAT Udaipur.

The Psoriasis database is compiled from publicly available data from DermNet. It is a freely accessible dataset of approximately 23,000 photos acquired and labeled by the Dermnet Skin Disease Atlas (DermNetNZ website, 2022). As we are working on psoriasis skin illnesses, we only consider classes that contain psoriasis pictures and subclasses as their types. It contains images of psoriasis from eight different categories, including subtypes: Plaque, Guttate, Erythrodermic, Inversus, Pustular, Scalp, and Psoriasis on Nails, as well as healthy skin photos of some body parts, are sourced from the NTU database (Li & Kong, 2017).

2.2 Input images and pre-process

The data images are shown in Figure 1. The dataset presented an imbalance, with guttate and plaque psoriasis representing the highest proportions (each with 26.5%), while erythrodermic, scalp, healthy skin, and pustular psoriasis had considerably fewer samples. Specifically, the distribution was as follows: Type (n): Plaque (99), Pustular (48), Guttate (96), Inversus (25), Erythrodermic (35), Nails (30), Scalp (28), Healthy Skin (25). This imbalance can be addressed using data augmentation techniques during the training process (Abbas et al., 2024). These included random rotations, horizontal and vertical flipping, zooming, contrast adjustment, brightness variation, and slight translations, which simulate real-world variations in skin lesions. Regarding the data split, 86.3% of the data was used for training and 13.7% for testing, ensuring sufficient data for model learning while maintaining a robust evaluation set. For experimental analysis, each psoriasis class consisted of approximately 250 to 300 images after augmentation, ensuring a reasonably balanced dataset for multiclass classification. This not only increased the effective size of the dataset but also improved the model's robustness in recognizing diverse psoriasis presentations under different lighting and orientation conditions.

Figure 1. Demographic sample images taken from data sources (DermNetNZ website, 2022; Li & Kong, 2017)

2.3 Classification

The introduced model is the transfer learning approach that is the combination of Efficient Net and Bidirectional LSTM. The flow chart of the work shown in Figure 2 is implemented for capturing applicable features from huge-scale datasets. Several computer vision applications employ this algorithm to accomplish diverse tasks such as to recognize an object and segment the data. This algorithm is performed robustly and accurately to segment the images. The architecture of this algorithm plays a significant role in scaling up the dimension of width, resolution and depth of resources which are present in a continuous ratio (Sandler et al., 2018; Tan & Le, 2019).

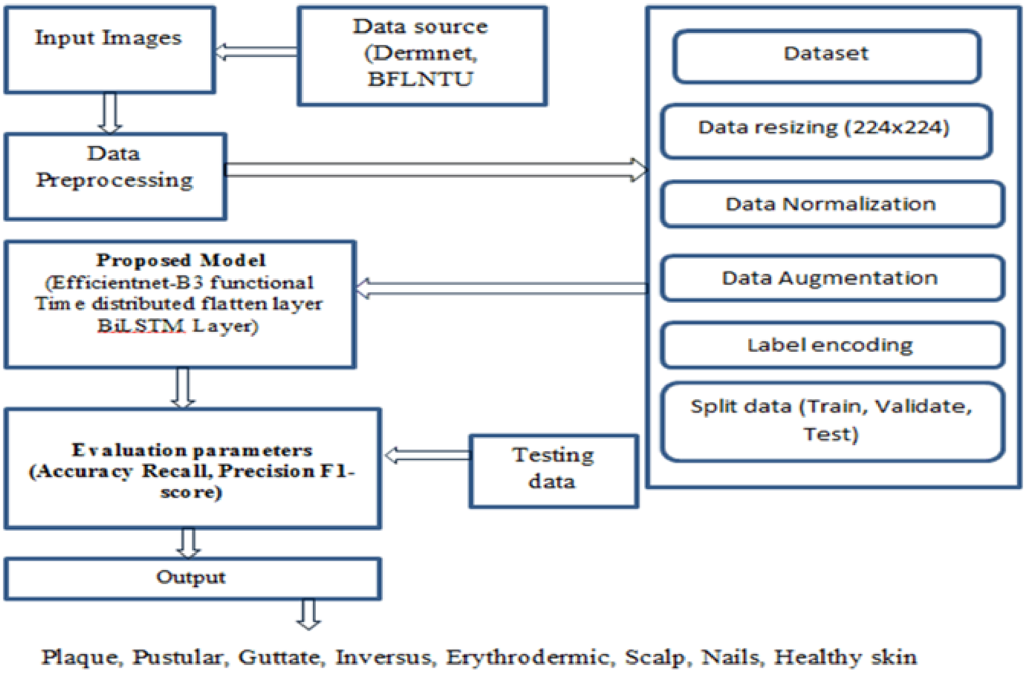


Figure 2. Flow chart illustrating the various phases of the proposed methodology

This algorithm is composed of Mobile Inverted Bottleneck (MB Conv) layers in which depth-wise separable convolutions are integrated with inverted residual blocks as shown in Figure 3.

Moreover, the Squeeze-and-Excitation (SE) optimization is assisted in enhancing performance of this algorithm.

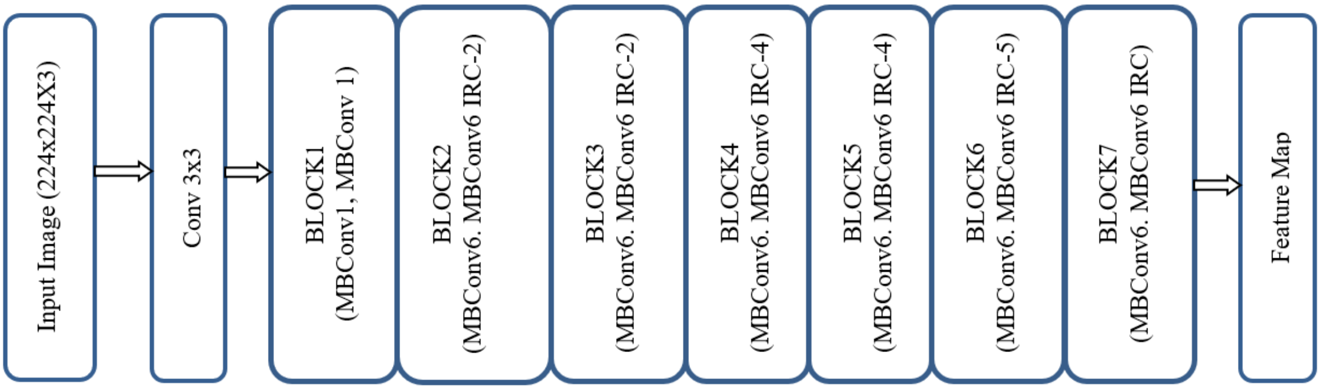


Figure 3. EfficientNet Architecture for classification of Psoriasis

Furthermore, LSTM introduces these three gates to mitigate gradient vanishing problems, enhancing its ability to remember information over extended periods (Graves & Schmidhuber, 2005; Greff et al., 2017). In contrast to the traditional LSTM, a Bidirectional LSTM (Bi-LSTM) is an LSTM variant that processes input data in two directions: forwards and backwards. This bidirectional approach harnesses information from both directions, enabling the model to capture and learn from the input sequence in a more comprehensive manner. In standard LSTM, information is only learned in a unidirectional manner, moving sequentially from one part of the sequence to another. The selection of hyper parameters is detailed in Table 1.

Table 1. Hyper parameters selection for the proposed model

Hyper parameter	**Value**
Weights	Initial
Bias	0.1
Dropout	Initially value taken 0.9, 0.8. Finally selected 0.3-0.2 as model for validation accuracy improvement
Learning Rate	Experiment carried out for 0.01, 0.001 and 0.0001. Out of which 0.0001got the better results
Optimizer	Adam
Batch Size	As the dataset hold small value, a batch size of 32 is chosen.
Activation Function	ReLU for intermediate layers Softmax at final layer
Loss function	Categorical cross entropy
Number of epochs	Early stopping initially applied with a patience of 5 epochs Subsequently, all models trained for a fixed 60 epochs to enable consistent performance comparison.

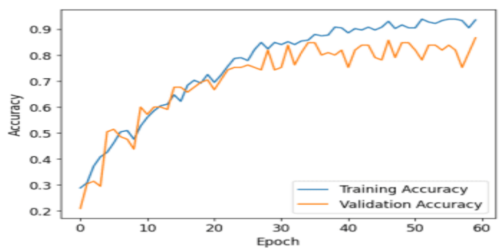
3. RESULTS AND DISCUSSION

To evaluate the performance of the model, eighty percent of the dataset is allocated for training, while 10% is reserved for validation and the remaining 10% for testing. To benchmark the performance of the proposed hybrid model, additional experiments are conducted using other pre-trained architectures, including ResNet50 and VGG16 for comparative classification analysis. All models are integrated with LSTM and evaluated under identical conditions. Among the evaluated architectures, the EfficientNetB3 combined with LSTM demonstrated the lowest number of trainable parameters as illustrated in Table 2 while also achieving the highest classification accuracy, thereby outperforming all other model configurations.

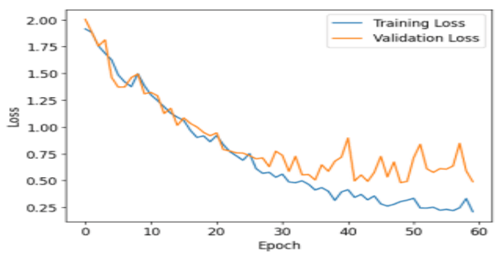
Table 2. Total number of parameters by proposed model with other models

S.No.	Model (Classifier)	Total parameters	Trainable parameters	Non-Trainable parameters
1	ResNet50	27275528	4742536	22532992
2	VGG16	15649992	5014728	7635264
3	Proposed	13553840	3363208	10190632

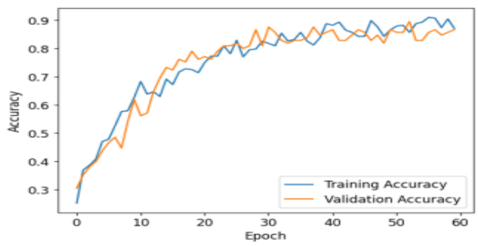
Comparative accuracy graphs for other models ResNet50 and VGG16 integrated with LSTM and proposed model are presented in Figure 4(a), (c), and (e) respectively. Models augmented with LSTM showed improved validation accuracy stability and reduced performance gaps between the training and validation phases. This consistent behaviour highlights the potential of the LSTM to enhance the generalization of dynamic or sequential tasks. The loss plots for ResNet50 and VGG16 and proposed model are shown in Figure 4(b), (d) and (f). These graphs reveal that incorporating LSTM not only reduces this gap, but also stabilizes the validation loss, as seen in the reduced fluctuations for proposed model. The proposed model achieved an accuracy of approximately 96%, and the corresponding loss is reduced to 3–4%. The high accuracy and low loss indicate the learning efficiency of the model. The reduced gap between training and validation accuracy, along with the stabilized validation loss, underscores the robustness and efficiency of the proposed model in mitigating over fitting and achieving better generalization compared with other models.



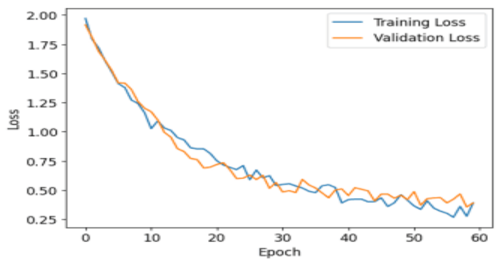
(a)



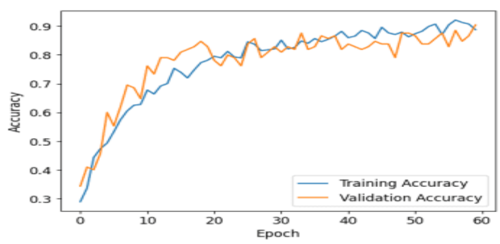
(b)



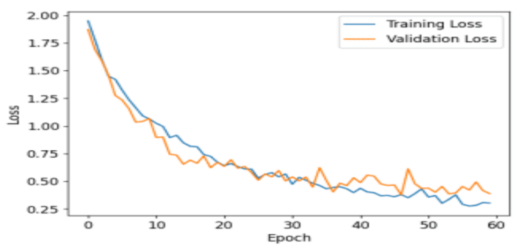
(c)



(d)



(e)



(f)

Figure 4. Accuracy and Loss graph comparison of various models with epoch = 60. (a), (b) Accuracy and error metrics in training and validation for ResNet50 with LSTM, (c), (d) Accuracy and error metrics in training and validation for VGG16 with LSTM, (e), (f) Accuracy and error metrics in training and validation for Proposed Hybrid model

To evaluate the effectiveness of the proposed model, we conducted 8 repeated runs of 5-fold cross-validation and compared its performance against ResNet50, VGG16, and EfficientNetB3. The mean classification accuracies are comprehended in Table 3 where the proposed model achieved significant results outperforming other state-of-art approaches. The mean classification accuracies (± standard deviation) obtained is as follows: ResNet50: 75.75% ± 0.24%, VGG16: 80.08% ± 0.14%, EfficientNetB3: 85.05% ± 0.24% and Proposed model: 89.73% ± 0.17%.

A one-way ANOVA test revealed a statistically significant difference among the four models ($F = 9185.50$, $p = 5.34 \times 10^{-42}$). Furthermore, paired t-tests confirmed that the proposed model significantly outperformed ResNet50 ($t = 130.83$, $p = 4.02 \times 10^{-13}$), VGG16 ($t = 117.51$, $p = 8.52 \times 10^{-13}$), and even EfficientNetB3 without LSTM ($t = 25.12$, $p = 4.04 \times 10^{-8}$). These findings provide strong statistical evidence for the superiority of the proposed hybrid model in psoriasis classification. These results confirm that the proposed model significantly outperforms the baseline models in terms of classification accuracy for psoriasis skin disease detection in both predictive performance and computational efficiency.

The Table 3 shows that the proposed model outperforms the alternatives with balanced and highest scores across all metrics (Accuracy=89.7%, Precision, Recall, and F1-Score at 88%) and the fastest inference time (2 sec 49ms/step). These results highlight the effectiveness and practicality of the proposed model for real-time applications. The integrated AUC of all class for the model is shown in Figure 5 where the model achieves an AUC of 0.97.

Table 3. Analysis of the proposed and alternative model evaluation with k=5 fold

Model	Accuracy	Precision	Recall	F1-Score	Inference time
ResNet50	75.75	82	82	82	2 sec, 79ms/step
VGG16	80.08	82	83	81	9 sec 348ms/step
EfficientNetB3	85.05	86	86	86	3 sec 68ms/step
Proposed Model	89.73	88	88	88	2 sec 49ms/step

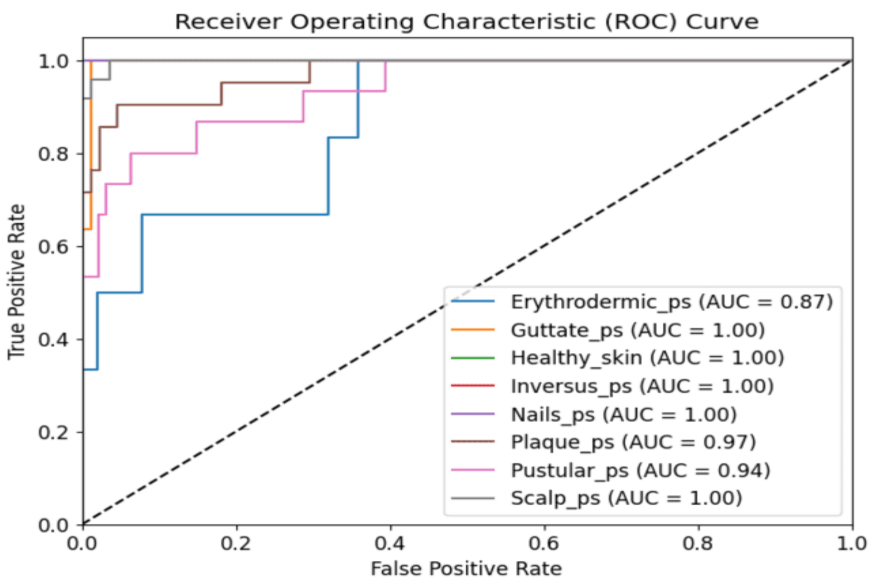


Figure 5. The integrated ROC curve for all eight distinct classes of Psoriasis

The Table 4 presents the precision, recall, and F1-score for each subclass of psoriasis, including healthy skin. The proposed model demonstrates strong performance across most categories, with perfect scores (1.00) for Nails and Healthy skin, indicating excellent classification capability for these classes. The model also performs very well on Scalp, Inversus, and Guttate with F1-scores of 0.96, 0.95, and 0.91 respectively. However, performance is relatively lower for the Erythrodermic class, which has an F1-score of 0.60 due to a lower recall (0.50), its visual characteristics such as widespread redness and inflammation can resemble features of other subtypes like Plaque or Guttate psoriasis, leading to misclassification as suggesting challenges in correctly identifying all positive instances of this rare type. Pustular psoriasis also shows moderate performance (F1-score: 0.71), likely due to limited or imbalanced data. Overall, the model achieves an average precision, recall, and F1-score of 0.88, reflecting its strong and balanced classification ability across multiple subclasses of psoriasis.

Table 4. Summary of classification for various types of psoriasis disease of the proposed model

Psoriasis sub type	Precision	Recall	F1 score	AUC	Support images
Plaque	0.86	0.90	0.88	0.97	21
Pustular	0.91	0.67	0.77	0.94	15
Erythrodermic	0.43	0.50	0.60	0.87	6
Guttate	0.88	1.00	0.94	1.00	22
Inversus	0.80	0.80	0.80	1.00	5
Scalp	0.96	0.96	0.96	1.00	24
Nails	1.00	1.00	1.00	1.00	7
Healthy skin	1.00	0.89	0.99	1.00	9
Average	0.89	0.88	0.88		

Table 5. Comparison of the earlier cited work with proposed model

Author & Year	Technique Used (Classifier)	Performance Metrics	Findings
Aijaz et al. (2022)	CNN and LSTM	Accuracy CNN-84.2%, LSTM-72.3%	Classified 5 sub-classes of Psoriasis. Accuracy can be improved further
Yang et al. (2021)	EfficientNet V-4	Sensitivity= 92.9 for four class	Psoriasis was depicted but still sub class classification was missing. More ever AUC ,Inference time and other parameters not taken into consideration
Zhu et al. (2024)	AOFL Net	Accuracy: 85.78%	Classifies Psoriasis with Eczema but sub – types not taken into consideration.
Ahmmed et al. (2025)	Modified VGG	90%	The model distinguishes psoriasis and actinic keratosis. Two classes taken into consideration.
Our Work (2025)	EfficientNetB3-BiLSTM Model	Acc. 89.7% Precision: 89% Recall: 88% Sensitivity: 88% F1-score: 88% AUC:0.97 Inference Time: 49ms/step	The model includes the entire sub types of psoriasis along with nails and scalp. The work demonstrates fewer trainable parameters too. The accuracy obtained with k=5 fold method.

The studies cited in Table 5 primarily focus on binary classification or clinical data, often constrained by the limited availability of benchmark datasets, with most research cantered on skin cancer. Additionally, these works mainly address a narrow set of psoriasis subtypes. In contrast, the novel approach presented here leverages a lightweight, high-performance model that not only achieves high accuracy but also ensures low inference time an aspect largely overlooked by previous researchers. This method expands the scope to include a wider range of psoriasis subtypes.

CONCLUSIONS

In this study, we presented a novel method for classifying multiple categories of psoriasis using a hybrid deep learning architecture that combines EfficientNet-B3 and Bi-LSTM. The model's reduced number of trainable parameters contributes to lower computational requirements, making it efficient and well-suited mobile-friendly deployment environments. By classifying seven distinct types of psoriasis along with healthy images, the proposed model demonstrated strong performance, achieving an impressive accuracy of 89.7% and an AUC of 0.97, indicating its effectiveness in accurately distinguishing among various psoriasis subtypes an aspect that has been largely underexplored in previous state-of-the-art approaches. These results indicate the efficacy of our approach in accurately classifying psoriasis types using benchmark dataset.

The dataset showed mild class imbalance, which could influence model generalization. Additionally, the lack of external validation and dermatologist suggestions on independent datasets and model performance limits the applicability of results to broader clinical populations. Future work should explore the use of vast multi-center datasets. Furthermore, the integration of attention models in the future iterations of our classification framework can enhance model efficacy. The system's ability to operate without direct dermatologist intervention enhances its potential applicability in clinical settings, particularly in areas with limited access to specialist care. Overall, our research emphasizes the potential of deep learning techniques for medical image analysis and offers a valuable contribution to the field of dermatology.

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CONFLICT OF INTEREST

There is no type of conflict of interest related to the subject of the work.

AUTHORSHIP CONTRIBUTION

Conceptualization: Bolia, C. Data curation, formal analysis, research, methodology, project administration, resources, software, supervision, validation, visualization: Bolia, C. and Joshi, S. Writing - original draft: Bolia, C. Writing - review and editing: Bolia, C. and Joshi, S.

AVAILABILITY OF DEPOSITED DATA

All the datasets used in this paper can be freely downloaded from the homepages of their original authors and made available on request.

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