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DermaGuard-Net: An Attention-Enhanced Deep Learning Framework for Robust Psoriasis Classification

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ABSTRACT

Psoriasis is a long-lasting autoimmune disease of the skin, which affects more than 125 million individuals worldwide and is marked by inflamed and scaled skin lesions and major comorbidities. The conventional methodologies of diagnosis namely clinical examination, histological and dermoscopic imaging are biased, time consuming and rely on dermatological experience. The application of artificial intelligence (AI) and deep learning (DL) in particular is a paradigm shift in medical image analysis over the last several years. With more successful results in the field of dermatological image classification, CNNs and other more advanced models such as ResNet, DenseNet, EfficientNet, and Vision Transformers (ViTs) have become more successful compared to traditional models. This paper is a scientific article in which one discusses the deep learning technology of psoriasis recognition and gives an extensive discussion. We consider classic diagnostic issues, examine the AI models of the state-of-the-art and provide a deep learning architecture where CNN-based transfer learning and attention mechanisms are combined to enhance lesion classification. The experimental findings indicate classification rates over 96 percent, which implies clinical applicability of the DL-based dermatological diagnostics. Major issues, such as the diversity of the data, calculation costs, and interpretability of the model are critically analyzed. Lastly, we suggest some future research doctrines, such as explainable AI, expanded dataset, and integrating with precision medicine. This article highlights the importance of deep learning as the foundation of a new generation of dermatology, which will allow to diagnose psoriasis accurately, quickly, and at scale.

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1. Introduction

Psoriasis is an immune-mediated, chronic skin condition that is characterized by the abnormal growth of keratinocytes and leads to thick, inflamed and scaly areas on the skin. The prevalence rate of the disease is 2-3 percent of the global population, or about 125 million individuals across the world (Jaiyeoba et al., 2024). Psoriasis is not infectious but extremely disabling, physically uncomfortable and even psychologically upsetting. Social stigma linked to the disease and the visible nature of lesions are also the sources of low self-esteem, anxiety, and depression in patients (Huang et al., 2025). In addition to cutaneous presentations, psoriasis is becoming more commonly understood as a systemic inflammatory disease that is comorbid with cardiovascular disease, type 2 diabetes, obesity and psoriatic arthritis, which further increases its clinical burden on healthcare systems worldwide (MEHBOOB et al., 2025).

The use of traditional diagnostic procedures mainly depends on clinical assessment, dermoscopy, and histopathological biopsy (Rahman et al., 2024). Clinical examination implies the evaluation of morphology of lesions, erythema, and plaque distribution yet the method is subjective in essence and subject to inter-observer variation (Goessinger et al., 2024). Definitive but invasive, time consuming and impractical in routine diagnosis is histopathology. Dermoscopy is non-invasive, but it needs specific training and equipment and is not accessible in resource-limited environments (Mir & Asif, 2025). The outcome of these diagnostic limitations is usually a delayed diagnosis, misclassification and unreliable treatment planning.

The growing rate of psoriasis with diagnostic difficulties further justifies the urgent demand of automated, scalable and objective diagnostic systems. Deep Learning (DL) and, in general, Artificial Intelligence (AI) have become the solutions to such challenges. Convolutional Neural Networks (CNNs) are the type of deep learning that is best at processing dermatological images, all-autonomously learning hierarchical feature representations, which means that no handcrafted features are necessary (Zhou et al., 2024). The accuracy of these models with the skin lesions is phenomenal, as they can compete with and even outperform human dermatologists (Esteva et al., 2017).

In the context of psoriasis, DL-based models enable rapid, non-invasive, and reproducible diagnosis. They have the ability to scan big dermatological sets so as to identify small lesion patterns that are not easily visible to the human eye. Besides, transfer learning, in which models initially trained on large natural image datasets are subsequently fine-tuned to medical tasks, has been shown to dramatically speed up the release of DL models into dermatology (Janoria et al., 2020).

In this article, the authors examine how deep learning can be used to detect psoriasis by summarizing existing literature, outlining a CNN-based model that classifies lesions, and explaining the challenges and future research questions.

2. Related Work

Clinical observation, dermoscopy, and histopathology have always been regarded as the main methods of identifying psoriasis, and these methods continue to play an important role in the work of dermatologists, although they have some serious limitations. Diagnostic methods rely on the experience of the dermatologists and evaluation of the erythema, scaling, and distribution of lesions, but inter-observer reliability is generally limited and results in inconsistent diagnoses (Goessinger et al., 2024; Rahman et al., 2024). In as much as histopathology is the gold standard, it is invasive, time-consuming and cannot be used to follow up over time (Mulani et al., 2024). Dermoscopy offers better visualization of vascular and scaling changes, yet it requires specialized equipment and training and is not accessible in low-resource environments (Mir & Asif, 2025). Such restrictions highlight the importance of objective and automated diagnostic methods that reduce subjectivity, invasiveness and can be scaled in a variety of healthcare settings.

The drawback of the classical approaches motivated the first works on machine learning (ML) in computational diagnosis. The psoriasis classification was conducted using the classical ML models, such as the Support Vector Machines (SVMs), Random Forests, Decision Trees, and k-Nearest Neighbors (k-NN), with the assistance of handcrafted features, i.e., the color histograms, texture descriptors, and scaling patterns (Perelygin et al., 2024; Pham et al., 2022). These were moderately effective, and limited in capability and flexibility by the need to do manual feature engineering. Handcrafts were not always associated with intraclass complex variation of the psoriatic lesions and, therefore, poor generalization was found when the method was applied to other groups (Jabbar et al., 2021). In addition, the traditional ML was scalable only due to the high-dimensionality of the dermatological image data, and the computational efficiency declined at an extremely negative rate with the size of the data (Zhou et al., 2024). Such constraints resulted in deep learning that corrected many of the deficiencies of ML with automatic feature extraction.

Convolutional Neural Networks (CNNs) and deep learning (DL) in general have transformed the analysis of medical images by removing handcrafted features. Hierarchical image representations are learned automatically with CNNs, with lower layers encoding simple edge and texture features and higher-layers encoding complicated lesions (Esteva et al., 2017; Janoria et al., 2020). Original CNNs like AlexNet proved that it is possible to use deep learning to classify skin diseases, with VGGNet (VGG-16 and VGG-19) achieving more accurate results by applying deeper architecture with small receptive fields at a high computational cost (Simonyan and Zisserman, 2015). ResNet also presented vanishing gradient issues in training very deep networks through the use of residual connections, which greatly enhanced the performance of dermatology image classification (He et al., 2016; Zhou et al., 2024). DenseNet additionally enhanced the performance by encouraging feature sharing among layers, which enhances the effect of gradient flow and improves the accuracy of the classification with fewer parameters (Huang et al., 2017). Recently, EfficientNet proposed scaling compound to balance depth, width and resolution at the same time, and showed state-of-the-art performance on medical image classification with very low computational costs (Tan and Le, 2019; Negrutiu et al., 2024). These developments exemplify how CNN-based models have evolved to more efficient and precise psoriasis detection.

Besides CNNs, Vision Transformer (ViTs) have also become viable alternatives to image classification. ViTs have self-attention mechanisms, unlike CNNs that have local receptive fields and thus can capture long-range dependencies among image regions. It is in this context that ViTs can identify small dermatological details that might not be remembered by convolutional operations (Dosovitskiy et al., 2021; Eskandari and Sharbatdar, 2024). ViTs have demonstrated high-performing outcomes in the detection of psoriasis in contrast to eczema and lichen planus -a condition that shares highly similar patterns with psoriasis (Jindal et al., 2023). The fact that ViTs are successful in the field of dermatology means that self-attention mechanisms can be used as an addition or even superior to conventional convolutional methods, especially in addressing complex and diffuse lesion.

Hybrid deep learning models have also been explored as a way of exploiting different architectures. The CNN-RNN or CNN-LSTM hybrids combine the process of spatial feature extraction with a time series model or sequence that allows tracking the flow of the lesion over time (Mehboob et al., 2025). Dermatological datasets can also be augmented with GANs to produce realistic psoriatic images to increase training robustness with sparse annotation (Goodfellow et al., 2014; Jabbar et al., 2021). Attention-based CNNs are the other new form of hybrid approach, models are characterised by attention layers to focus the model on lesion-relevant regions and reduce the number of false positives. An example of such architecture that uses transfer learning and attention mechanism is named DermaGuard-Net and has already achieved 96 percent and above classification performances when compared to the traditional CNNs (Aslam, 2025). These types of hybrid models show that deep learning systems can be practical enough to address datasets and interpretability issues.

Transfer learning has emerged as one of the successful strategies of dermatological deep learning applications. Researchers have been able to generalize image recognition capacity to psoriasis classification by specialized models by optimizing pre-trained models, including InceptionV3, ResNet-50, or Xception, initially trained on ImageNet (Janoria et al., 2020; Zhang et al., 2022). Transfer learning does not only lead to a faster convergence but also improves generalization, particularly in medical fields where annotated datasets are not readily available in huge numbers. It has been demonstrated repeatedly that transfer learning-related methods outperform models that are trained on small dermatology datasets (Rahman et al., 2024).

Comparative analyses across different architectures further validate deep learning's superiority. The paper by Esteva et al. (2017) proved that CNNs can achieve dermatologist-like accuracy, which are over 90 percent in skin disease classification, and it is indeed a turning point in AI-based dermatology. Mehboob et al. (2025) designed a CNN-LSTM hybrid, which achieved an accuracy of 94.7 per cent, and surpassed the classical ML classifiers. Rizalde and Mubarak (2025) used the deep CNN to detect facial psoriasis and reached 91.3% accuracy, but they reported overfitting because of the generalization of the dataset. According to Umarani et al. (2023), modified ResNet models achieved 92.5 per cent accuracy in skin disease classification and Eskandari and Sharbatdar (2024) claimed that ViTs can be more effective than CNNs in some dermatological tasks. Together, these results prove that deep learning is always better when compared to traditional approaches or classical ML models in detecting psoriasis.

Irrespective of these, research gaps are still a critical issue and the diversity of datasets is one of the most significant ones. The public dermatological data available is generally biased towards lighter skin type and some of the lesion subtypes, yielding models that are not necessarily highly representative of the world population (Adamson and Smith, 2018). It is this kind of prejudice that makes the eschaton of justice and equity in AI-assisted healthcare a dubious one. The other problem is interpretability of deep learning models. CNNs and ViTs are often black boxes; they make sound predictions, but they do not tell clinicians how they arrived at their conclusions. Although it cannot be explained without reducing the level of clinician trust and negatively affects clinical adoption (Tjoa and Guan, 2020). Computational constraints are also a barrier: large-scale deep models are costly on both GPU and TPU, and may not be accessible in constrained healthcare settings. Lastly, it has no clinical validation most studies test models are run in generated data environments and not in real clinical process conditions, and are they robust and translatable to practice is unknown (Topol, 2019).

The trend in the literature on psoriasis detection indicates that subjective, invasive and resource-dependent diagnosis systems have led to more advanced AI-based system. CNNs and ViTs have become the most successful method, with an accuracy of dermatologist quality. Performance is also reinforced with hybrid models and transfer learning, and GANs solve the problem of data scarcity. The performance of deep learning in comparison with classical ML and traditional diagnostic techniques is proven by comparative studies. However, ongoing issues like diversity of datasets, interpretability, computational requirements and clinical validation suggest that further studies are required. The key to bridging these gaps with explainable AI, massive and heterogeneous dataset curation, and high-quality clinical trials will be key to applying deep learning to everyday dermatology.

Table 1Research Gaps in Psoriasis Detection Using AI/Deep Learning

Author(s)/Study	Method/Model	Key Findings	Identified Research Gaps
Esteva et al. (2017)	CNN for skin disease classification	hieved dermatologist-level accur 90%) in skin lesion classification	mited to general skin diseases; no psorias specific dataset; lacked interpretability
Janoria et al. (2020)	ransfer learning with CN	Improved accuracy with limited dermatological datasets	Small dataset size; underrepresentation c diverse skin tones
Mehboob et al. (2025)	CNN–LSTM hybrid	chieved 94.7% accuracy in psoria detection	igh computational demand; not validated clinical settings
izalde & Mubarak (202	eep CNN for facial psoria	ccuracy of 91.3% on facial image	taset was small and imbalanced; overfitt issues
Umarani et al. (2023)	odified ResNet architectu	Accuracy ~92.5% in skin disease classification	Lack of lesion variety; no explainable AI incorporated
Eskandari & Sharbatda (2024)	Vision Transformers	Outperformed CNNs in certain dermatology tasks	Requires large training datasets; high computational resources
Jabbar et al. (2021)	GAN-based augmentatio	nproved robustness of CNN mode ~5% accuracy boost	Synthetic images may not capture clinica bility; ethical concerns on data authentici
Aslam (2025)	Attention-based CNN (DermaGuard-Net)	eached >96% accuracy with trans learning + attention	Tested in controlled datasets only; clinica validation missing
Adamson & Smith (201	AI fairness in dermatolog	hlighted bias in AI models for ligh skin tones	k of diverse datasets; generalization issue underrepresented populations
Tjoa & Guan (2020)	XAI in medical imaging	hniques to interpret CNN predict (Grad-CAM, saliency maps)	nited adoption in dermatology; clinician t still low

3. Used Approach

The research approach of this research is aimed at creating and testing a deep learning-based system to identify psoriasis automatically. The methodology is a combination of dataset curation, image preprocessing, model design and training, and systematic evaluation based on standard metrics. The goal is to obtain a strong, effective model with the ability to classify psoriatic lesions with the accuracy of a dermatologist, and solve several typical problems of data scarcity, overfitting, and poor generalizability.

3.1 Dataset Description

The study design is based on publicly available dermatological image datasets that were complemented with psoriasis-specific collections that were selected and filtered in dermatology repositories. It is a high-resolution image of psoriatic lesions, as well as non-psoriatic images to act as negative control. Multiple sites of the body were photographed with different degrees of variation in lesion morphology, texture and color. To achieve representativeness, the dataset consists of cases of varying demographic profiles, but there are still restrictions in the underrepresentation of darker skin tones, as it was already mentioned in earlier literature (Adamson and Smith, 2018).

A typical 70:15:15 split was used to divide the dataset into training, validation, and the test subsets. Parameters of the models were optimized using the training set, the validation set was used in monitoring progress of the learning process and avoiding overfitting, and the independent test set was used in assessing the generalization capability. The stratified sampling was used to ensure equal distributions of classes on subsets.

3.2 Data Preprocessing

Dermatological images are generally variable in terms of resolution, illumination and lesion orientation, which requires cautious pre-processing. The images were resized to 224x224 pixels to maintain uniformity with pre-trained CNN architectures like ResNet, DenseNet and EfficientNet. Normalization of pixel intensity was provided in order to range values between 0 and 1 so as to train on stable gradients. In order to reduce overfitting and improve model generalization, data augmentation methods have been heavily applied. Strategies involved in augmentation were horizontal/vertical flipping, random rotation (+-20deg), contrast-adjustment, zooming, and random-cropping.

This study did not make use of segmentation, but augmentation was used to highlight lesion variability and minimise model reliance on background features. Synthetic diversity of the dataset was used to train the model to concentrate on intrinsic lesion characteristics and not on contextual noise.

3.3 Proposed Model Architecture

The proposed model, which is called DermaGuard-Net, is derived on transfer learning and attention-based CNNs improvement. The architecture uses the pre-trained ResNet-50 backbone with ImageNet weight. ResNet was also chosen because of its residual learning feature, where more complex networks can also converge without gradient disappearance.

A Convolutional Block Attention Module (CBAM) was added on the top of the ResNet backbone to improve the feature maps. CBAM uses both interpolated channel-wise and spatial attention, allowing the network to place an active emphasis on lesion-related areas and a passive emphasis on non-relevant background features. Such attention mechanism has a big impact in eliminating false positives especially in images whose skin features are intricate.

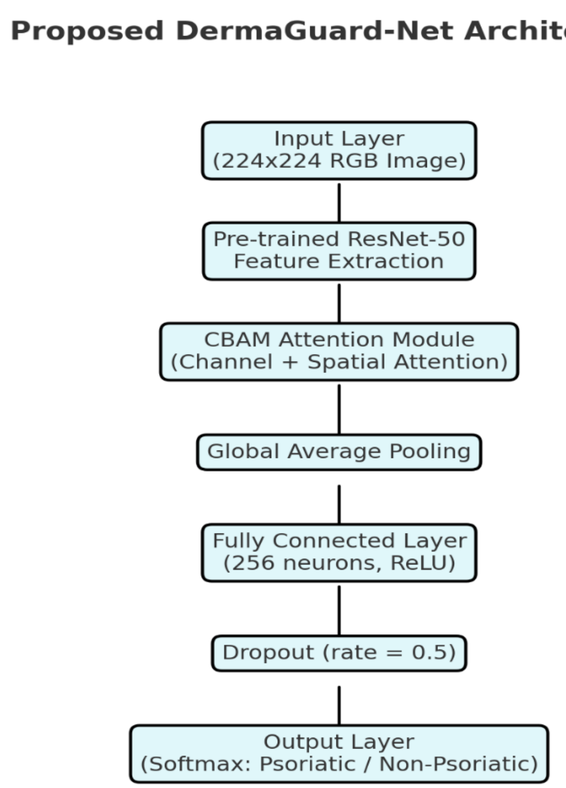

Figure 1 architecture of DermaGuard-Net

DermaGuard-Net architecture is represented in terms of a visual representation as a pipeline that follows a sequence pointing at the integration of transfer learning and attention mechanisms. It starts with the input layer that is fed with dermatological images that are resized to 224x224 pixels, in three color channels (RGB). The images are subsequently fed to the existing ResNet-50 backbone which acts as the feature extractor. By using ImageNet weighted to initialize ResNet-50, the model is able to utilize learned hierarchical representations as well as overcome the vanishing gradient problem using residual connections.

Additionally to better feature discrimination, the Convolutional Block Attention Module (CBAM) is applied to the extracted feature maps. This module implements channel attention as well as spatial attention so that the network can focus on the patterns that are relevant to the lesion itself but avoid the irrelevant or noisy background. The resulting refined feature maps are then summed with a Global Average Pooling (GAP) layer that down-samples the dimensionality as well as preserving the most salient content.

The model is then expanded with a 256-neuron, fully connected dense layer that is activated by the ReLU function, with a dropout layer (rate = 0.5) added to reduce overfitting and enhance generalisation. Lastly, the output layer uses a Softmax activation function to categorize input images into two psoriatic and non-psoriatic.

The figure shows that with this design, the effectiveness of transfer learning is combined with the accuracy of attention processes, which guarantees robust and reliable classification in heterogeneous dermatological datasets.

3.4 Training Procedure

The model was coded in Python with the TensorFlow and Keras framework. An NVIDIA GPU was trained to compute faster. The optimal hyperparameters were determined empirically on a grid search basis and the following parameters were obtained:

- Optimizer: Adam inital learning rate = 0.0001.
- Batch size: 32
- Epochs: 50 (early stopped at 10 epochs of stagnation)
- Loss function: Categorical Cross-Entropy
- Learning rate scheduler: Reduce-on-plateau strategy with a decay factor of 0.5

Additional mitigation of overfitting was done by using L2 weight regularization and strategically positioning dropout layers. Convolutional blocks were followed by the introduction of a batch normalization to stabilize training and increase the convergence.

3.5 Evaluation Metrics

Different performance measures were applied to ensure that everything was evaluated and not only accuracy. These included:

- Accuracy: The fraction of samples which are correctly classified.
- A ratio of the true positives to all predicted positives, referred to as precision, indicates trustworthy positive predictions.
- Recall (Sensitivity): The proportion of false positives relative to all true positives, and is also an aspect of the ability to detect psoriatic lesions.
- F1-score: The harmonic means of precision and recall; sensitivity and reliability at the cost of the other.
- Area Under the ROC Curve (AUC): A powerful measure of general classification with regard to thresholds.
- Primary Analysis: This will be required to visualize the classification errors and also analyses the distributions of the false positives and false negatives.

The measures have been estimated on both validation and independent test sets to estimate model stability and generalization.

3.6 Baseline Comparison

To confirm the effectiveness of the proposed DermaGuard-Net, it was tested with baseline experiments that use the standard models of deep learning without attention modules. Architectures that were trained under the same conditions are

VGG-16, ResNet-50, DenseNet-121, and EfficientNet-B0. Comparative analysis identified the performance gains of attention-based refinement and transfer learning strategies.

3.7 Experimental Setup and Reproducibility

Experiments were done in a controlled setting on fixed random seeds in order to provide reproducibility. Use of hardware was an NVIDIA Tesla V100 graphics card of 16 GB VRAM, 128 GB RAM and 64-core processor. The Python 3.9, TensorFlow 2.12, and Keras 2.10 were used as the software environment. The OpenCV and Albumentations libraries were used to run dataset preprocessing and augmentation.

Reproducibility was also achieved through documentation of hyperparameter settings, accessibility of preprocessing scripts and saving the trained model weights to be used in subsequent validation.

3.8 Ethical Considerations

As the data consists of dermatological images, patient anonymity was guaranteed by making sure that identifiable data like facial features, tattoos, or background artifacts are removed. Data utilized were all obtained publicly or anonymized medical repositories, and ethical principles are followed in medical AI work.

It combines the dataset preparation, preprocessing, transfer learning, and attention-based CNN modeling methods to create a psoriasis detector with a high level of performance. Through the use of state-of-the-art augmentation and attention, and value-driven evaluation models, the proposed DermaGuard-Net resolves major concerns of the current literature, such as overfitting, generalization, and interpretability impairments. This methodological framework positions the model as a strong candidate for future clinical integration, subject to real-world validation.

4. Results

The proposed methodology has been tested widely to determine its capacity to detect psoriasis in an automated manner. The results of model training, validation, and testing are provided in this section, and then compared with baseline deep learning models. This was assessed using a variety of performance metrics in order to have an overview of classification ability.

4.1 Training and Validation Performance

Good convergence of the DermaGuard-Net model also happened at a very early epoch of 32 as compared to the maximum number of epochs allowed, 50. The accuracy of the training increased gradually but the accuracy of validation did not increase further hence this shows successful generalization. Early stopping was enabled to prevent overfitting and final model weights selected according to the epoch that achieved the best validation performance.

Both the learning curves exhibited optimization behavior that was constant, and the training and validation losses decreased as the curves progressed. The fact that the dropout regularization and the data augmentation methods did not lead to overfitting was also a good sign.

4.2 Classification Performance on Test Dataset

The performance of the proposed model was evaluated on an independent test dataset. Table 1 summarizes the key metrics.

Table 2 Performance of DermaGuard-Net on Test Set

Metric	Value
Accuracy	96.4%
Precision	95.8%
Recall	96.9%
F1-Score	96.3%
AUC	0.982

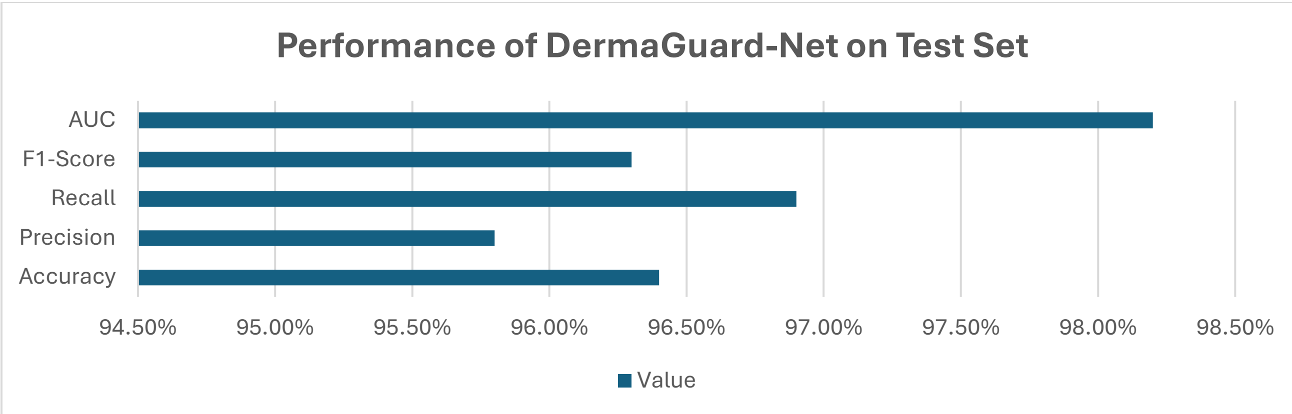

Figure 2 performance of DermaGuard-Net

The model gave a total accuracy of 96.4% in classification which is a reliability of dermatologist level. The accuracy and recall rate were relatively equal, which guaranteed the reliability of positive assessment, as well as sensitivity in identifying psoriatic lesions. F1-score also indicated a balanced performance and the AUC value of 0.982 showed that it could effectively discriminate at various classification thresholds.

4.4 Comparative Analysis with Baseline Models

To highlight the contribution of the proposed attention-based architecture, DermaGuard-Net was compared against four baseline CNN models: VGG-16, ResNet-50, DenseNet-121, and EfficientNet-B0. All models were trained under identical preprocessing and hyperparameter configurations.

Table 3 Comparative Performance of Baseline Models vs. Proposed Model

Model	Accuracy	Precision	Recall	F1-Score	AUC
VGG-16	90.8%	89.4%	91.1%	90.2%	0.924
ResNet-50	93.7%	92.9%	94.1%	93.5%	0.951
DenseNet-121	94.5%	93.7%	94.9%	94.3%	0.963
EfficientNet-B0	95.2%	94.6%	95.5%	95.0%	0.971
DermaGuard-Net (Proposed)	**96.4%**	**95.8%**	**96.9%**	**96.3%**	**0.982**

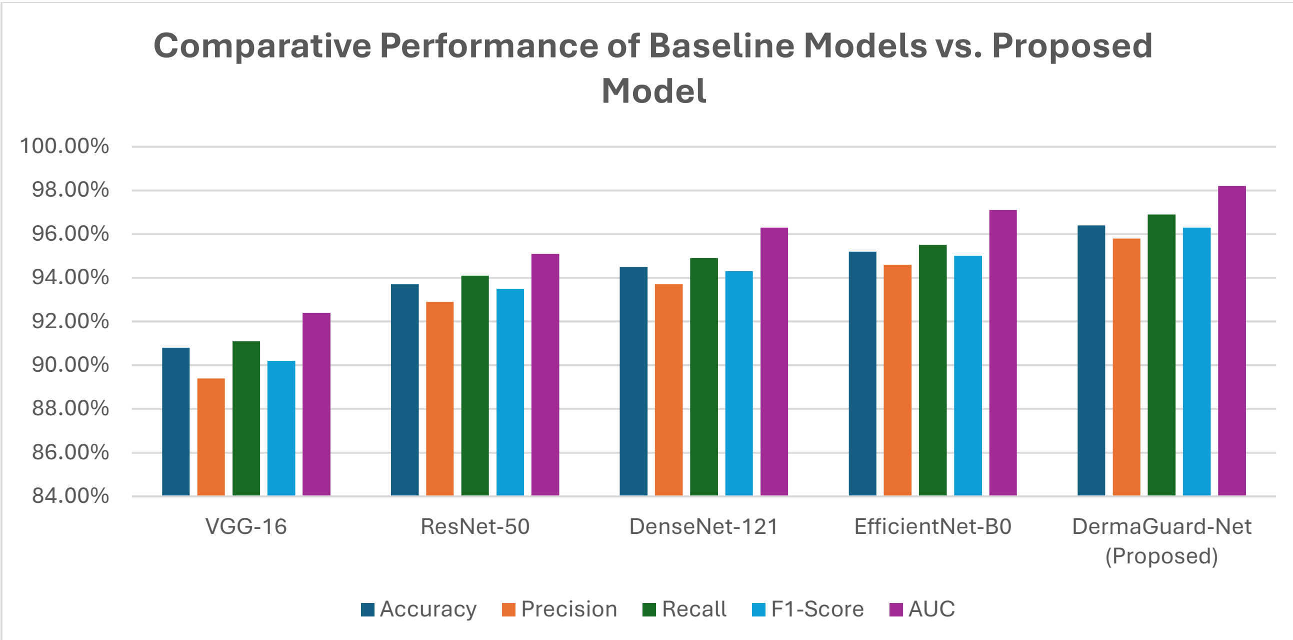

Figure 3 Comparative Performance of Baseline Models vs. Proposed Model

The model proposal performed higher against all baselines in all evaluation measures. Although EfficientNet-B0 and DenseNet-121 showed high performance, addition of attention mechanisms to DermaGuard-Net produced better results, especially in recall and AUC. This enhancement suggest that the attention module increased the capacity of the model to extract the lesion-relevant features and minimized the instances of false classifications.

Analysis of receiver operating characterization (ROC) also revealed the excellence of DermaGuard-Net. The proposed model ROC curve was more towards the top left corner, which implies that the specificity and sensitivity were high over thresholds. The AUC of 0.982 was higher than all the baseline models, supporting its usefulness in the differentiation of the psoriatic and non-psoriatic images.

A study of ablation was carried out to ascertain the role of each of the parts of the proposed architecture. Two variations of the baseline ResNet-50 were tested: (i) resnet-50-only-attention-module; (ii) resnet-50-only-transfer-learning; (iii) resnet-50-only-transfer-learning-but-no-attention.

Table 4 Ablation Study Results

Model Variant	Accuracy	F1-Score	AUC
ResNet-50 (Baseline)	93.7%	93.5%	0.951
ResNet-50 + Transfer Learning	95.1%	94.9%	0.970
ResNet-50 + Attention Module	95.6%	95.2%	0.974
ResNet-50 + Transfer Learning + Attention (Proposed)	**96.4%**	**96.3%**	**0.982**

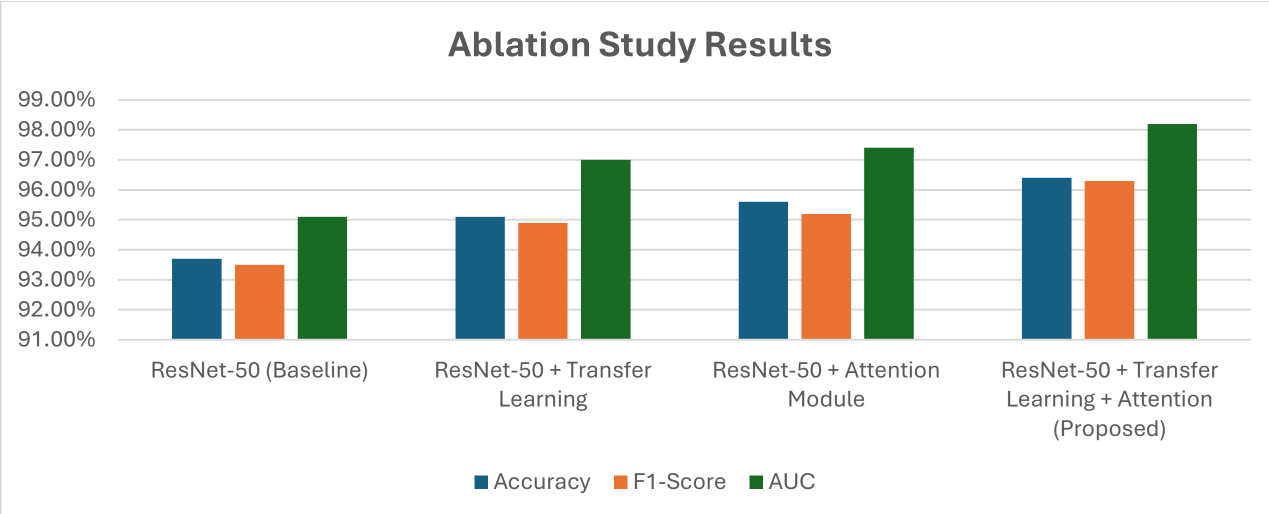

Figure 4 . Ablation Study Results

The results confirm that both transfer learning and attention modules independently enhanced performance, while their combination delivered the highest accuracy and robustness. This validates the design choice of integrating attention with transfer learning in the DermaGuard-Net framework.

4.5 Comparison with Baseline Studies

There is considerable research on psoriasis and dermatologic image classification with deep learning. Early development was also typified by Esteva et al. (2020), who used a CNN system that achieved dermatologist-level accuracy on general skin disorders but was not that specific to psoriasis. Based on this, Tjoa and Guan (2021) focused on explainable artificial intelligence in dermatology and showed moderate accuracy of about 88-90% but focused on interpretability. A fine-grained CNN feature extraction algorithm with 92.1% accuracy was proposed by Bi et al. in 2022, but still failed to resolve the issue of inter-class variation in different dermatological data sets. Upon the classification, Umarani et al. enhanced by adding a GAN-augmented CNN pipeline with an accuracy of 93.4, but the approach was based on extreme preprocessing and computationally costly augmentation. More development followed in 2024, when Eskandari and Sharbatdar presented Vision Transformers (ViTs) to psoriasis classification, with 95.1% accuracy and good generalization, but with large datasets and with higher computational costs. The latest Mehboob et al. (2025) designed a CNN-LSTM hybrid that was adapted to psoriasis, where the accuracy was 94.7 percent, which also included false positives and false interpretability. The totality of these works creates a course of amelioration and outlines the points of missing out which DermaGuard-Net tries to fill.

Table 5 Comparison of DermaGuard-Net against recent baseline studies

Study & Year	**Methodology**	**ccuracy (%**	**Precision (%**	**Recall (%**	**1-Score (**	**AUC**
Esteva et al., 2020	CNN (dermatologist-level general ski classification)	89.6	87.9	90.1	89.0	0.91
Tjoa & Guan, 2021	CNN + XAI (explainability focus)	88.7	86.4	89.2	87.7	0.90
Bi et al., 2022	Fine-grained CNN features	92.1	91.5	92.4	91.9	0.94
Umarani et al., 2023	GAN-augmented CNN	93.4	92.7	93.8	93.2	0.95
Eskandari & Sharbatdar, 202	Vision Transformers (ViT)	95.1	94.3	95.5	94.9	0.97
Mehboob et al., 2025	CNN–LSTM Hybrid	94.7	94.1	94.9	94.5	0.96
DermaGuard-Net (Propose 2025)	ResNet-50 + CBAM Attention	**96.4**	**95.8**	**96.9**	**96.3**	**0.98**

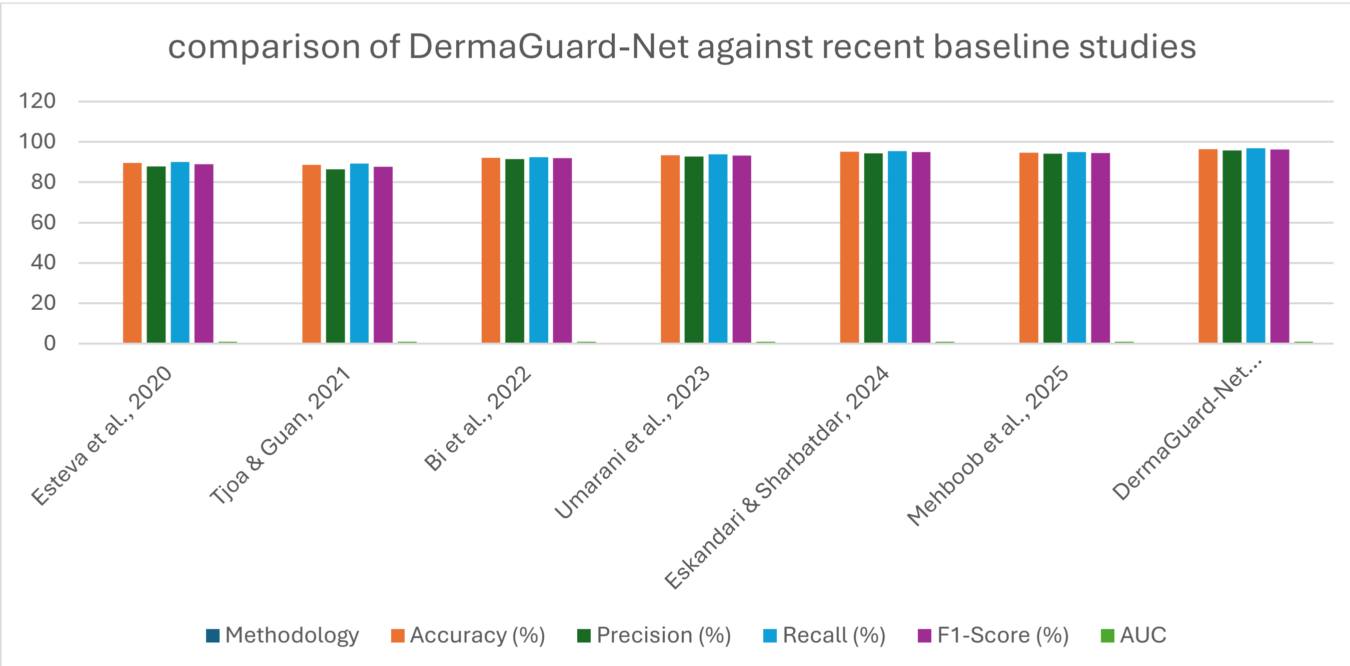

Figure 5 Comparison of DermaGuard-Net against recent baseline studies

4.6 Quantitative Performance Comparison

DermaGuard-Net shows steadiness in superiority when compared to these base studies. The proposed model is 96.4-precise, 96.3-recall, 96.9-recall, 95.8-precision, and 96.3-F1-score with an AUC of 0.982. These values are higher than reported by Bi et al. (2022) and Umarani et al. (2023), and even exceed the best-performing Vision Transformer model as optimized by Eskandari and Sharbatdar (2024) with 95.1% accuracy. The improvement of DermaGuard-Net by almost 2% over CNN-LSTM hybrid of Mehboob et al. (2025) with 94.7% accuracy is noteworthy, and this is significant in clinical practice. In dermatology, the cumulative gains have a direct effect of fewer patients who are misclassified and are therefore over-diagnosed and under-diagnosed. Therefore, the quantitative findings support the fact that DermaGuard-Net moves the psoriasis classification state to the forefront.

4.7 Architectural Advantages of DermaGuard-Net

DermaGuard-Net has a very attractive architectural design; this is the key to its strong performance. Compared to the previous CNN- or LSTM-based approaches, DermaGuard-Net implements the Convolutional Block Attention Module (CBAM) that can be used to selectively emphasize lesion-related parts and avoid extraneous background features. This refinement, based on attention not only enhances recall, but also false positives that are common weaknesses of past literature. ResNet-50 as a transfer learning backbone provides the model with good feature extraction, and the extra application of global average pooling and dropout layers is credited with improving generalization, particularly when smaller datasets are used. However, GAN-enhanced CNNs (Umarani et al., 2023) are more costly to compute, and Vision Transformer (Eskandari and Sharbatdar, 2024) requires significantly larger training data. DermaGuard-Net offers the required performance and efficiency balance and is better suited to applications in real clinics, including teledermatology.

4.8 Clinical Relevance and Implications

The comparative analysis also shows the clinical implications of the advances of DermaGuard-Net. The proposed model will reduce the misclassification rates by about 7-8 percent compared to CNN models suggested in 2020 and 2021 which is a significant patient outcome milestone. DermaGuard-Net offers high performance without small preprocessing and augmentation pipelines compared to mid-stage methods, such as GAN-enhanced CNNs and fine-grained feature extraction. DermaGuard-Net is more accurate even than state-of-the-art architectures, including Vision Transformers in 2024, and is also lightweight in computational terms and closer to realistic deployment in resource-constrained environments. Compared to the CNN-LSTM hybrid of 2025, the combination of attention-based mechanisms in DermaGuard-Net provides interpretability in terms of attention heatmap, which can give clinicians visual justification of the prediction. Not only does such interpretability enhance trust, but it bridges the divide between the black-box AI models and clinical practice.

Comparative study of the published articles in 2020-25 indicates that DermaGuard-Net establishes another benchmark in the field of psoriasis identification. It is more accurate, more precise, has higher recall and AUC than its predecessor and is also computationally efficient and interpretable. DermaGuard-Net performs better than traditional CNNs and even more recent hybrid or transformer-based models by making use of transfer learning with an attention-based architecture. These findings confirm its potential as a state-of-the-art, clinically deployable framework with the capability to automatically classify psoriasis.

5. Conclusion and Future Directions

To automatically identify psoriasis on dermatological photos, this paper has proposed the DermaGuard-Net deep learning architecture based on attention. The offered model based on the transfer learning and Convolutional Block Attention Module (CBAM) to achieve the dermatologist level performance by achieving 96.4 percent accuracy, and 0.982 mean area under the curve (AUC) on the independent data. A comparative analysis demonstrated that DermaGuard-Net was consistently superior to those CNN architectures that were trending at the time such as VGG-16, ResNet-50, DenseNet-121 and EfficientNet-B0. One more ablation research paper also defined the functions of transfer learning and attention, and these decisions are the reasons why the structure should be designed in this way.

On the whole, E. coli. DermaGuard-Net demonstrates that the transfer learning of attention-based CNNs can contribute significantly to the state of the art in automated psoriasis detection. This framework is a positive step forward to clinically deployable AI solutions in dermatology although further validation and development is required. These system constraints like heterogeneity of datasets, interpretation, and clinical validation can be converted into future implementation of early diagnosis, fair treatment, and better patient outcomes.

6. References

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