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Papulosquamous SkinSense: a hybrid artificial intelligence model with visual explanations and chatbot

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ABSTRACT

Accurate diagnosis of papulosquamous skin diseases such as Psoriasis (PS), Lichen Planus (LP), Pityriasis Rosea (PR), and Pityriasis Rubra Pilaris (PRP) is challenging due to their visually similar features, particularly during healing stages. This study presents an optimized deep learning framework to improve diagnostic accuracy and interpretability. A dataset of 3,120 DermsNetZ images was used, with preprocessing through contrast limited adaptive histogram equalization (CLAHE) to enhance lesion visibility. Pretrained convolutional neural networks (CNNs) including MobileNetV2, InceptionV3, NASNet, and hybrid models were evaluated using accuracy, precision, recall, and F1-score. Among these, MobileNetV2 combined with gradient-class activation mapping (Grad-CAM) achieved the best results, delivering 94% accuracy, 95% precision, and strong F1-scores, while offering explainable artificial intelligence (AI) through lesion localization. To translate these results into practice, the SkinSense Detection App was developed, integrating with transfer learning, class balancing, augmentation, and Grad-CAM visualization within a user-friendly interface. The app also incorporates a large language model (LLM-powered) chatbot for real-time, personalized feedback. With an overall success rate of 98.08% and user ratings between 4.6–4.8/5, the system demonstrates high reliability and accessibility. This study highlights the value of interpretable deep learning in dermatology, bridging technical accuracy with clinical usability and offering scope for expansion to larger datasets and diverse skin conditions.

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1. INTRODUCTION

The human body exists with multiple limbs and organs inside protective skin which functions as both immune system support and a defensive barrier. The skin protects the body by blocking pathogens and controlling water loss while functioning as the main protective defense against health problems [1]. Skin diseases operate as one of the major infectious disease categories that affect the worldwide population [2]. Projected data from the World Health Organization (WHO) shows that serious skin related conditions will affect 49.5% of Asian men and women by 2020 [3]. Research shows Bangladesh has become a victim of 384 skin disease related deaths [4]. Existing studies show skin-related deaths now number 9.6 million worldwide [5]. Human being experiencing skin disease develops clear surface and color changes that affect their skin's appearance. Skin diseases emerge principally from viral infections and bacterial infections together with fungal infections and allergic reactions according [6]. The rapid growth of urban populations and limited

public awareness of skin health have increased dermatological disease burdens [5], [6]. Healthy skin not only enhances appearance but also defends against infections and environmental hazards. Maintaining hygiene and environmental cleanliness is vital for preventing many skin disorders. Diagnosing these diseases often requires professional expertise, as overlapping symptoms such as redness, scaling, and itching make differentiation difficult [7]. Financial constraints further restrict timely care in low-resource settings. Artificial intelligence (AI) offers a transformative solution by enabling cost-effective, accurate, and rapid skin disease diagnosis. Through image analysis, AI systems especially convolutional neural networks (CNNs) can classify skin conditions by evaluating color, texture, and surface features with high precision. Among noninfectious diseases, Psoriasis (PS), Lichen Planus (LP), Pityriasis Rosea (PR), and Pityriasis Rubra Pilaris (PRP) are major papulosquamous disorders that pose diagnostic challenges due to their similar clinical presentations. PS typically affects elbows, knees, scalp, and trunk with persistent scaly lesions, while LP and PRP involve more complex manifestations requiring specialized treatment [8]. The DermCDSM model, built on a convolutional deep spiking neural network (CD-SNN) optimized using an improved chameleon swarm optimization (ICSO) algorithm, shows high diagnostic accuracy using the ISIC 2017 dataset [8]. Such AI-driven systems enhance early detection and classification, though maintaining accuracy remains difficult due to image variability and diverse disease patterns [9], [10]. This study addresses the challenge of accurately classifying clinically overlapping visual features, class imbalance, limited interpretability, and poor mobile optimization for papulosquamous skin diseases, including PS, LP, PR, and PRP [11]. Table 1 shows previous studies investigated standard deep learning models such as MobileNetV2, NASNet, and U-Net for skin lesion classification, they did not explicitly consider the impact of integrating explainable AI gradient-class activation mapping (Grad-CAM) for improving both diagnostic reliability and interpretability [11], [12].

This research paper solves the problems associated with traditional analysis methods including the invasive biopsy test that sometimes produces wrong results. This research highlighted the problems of prior machine learning methods which use manual physical characteristic retrieval techniques for detecting skin conditions. This study compares deep learning models, including MobileNetV2, InceptionV3, NASNet, and hybrid architectures, using metrics like accuracy, precision, recall, and F1-score. Through MobileNetV2 transfer learning the research introduces a weight optimized framework that automates the classification of papulosquamous skin lesions [13], [14]. This paper shows optimization of MobileNetV2 model in applying healthcare image data which is available on DermNetZ and Kaggle databases which contain 23 different skin conditions [15]-[25].

Table 1. Comparison of literarture reviewed with existing papers

Ref.	Technique/model used	Identified research gap
[11]-[14]	ResNet-RNN hybrid for PS, acne, and eczema	Lacked real-time deployment and explainability.
[15]	CNN for color and pattern recognition in skin images	Limited to surface-level feature extraction; poor generalization.
[16]	CNN to classify 6 conditions (vitiligo and acne)	Low accuracy (81.75%) and poor performance in visually similar diseases.
[17]	CNN+MobileNetV2 for Android detection	Limited to skin cancer only; ignored papulosquamous class.
[18]	MobileNetV2-LSTM for healthcare data	Focused on transmission security rather than model interpretability.
[19]	Grabcut segmentation for lesions and K-means clustering on psoriatic lesions	Only used thresholding; lacked deep learning integration. Difficulty in dynamically assessing lesion changes over time.
[22]	SVM, RF, ResNet50, VGG19+XGBoost on DermNet, and VGG-16	Varied model performance; hybrid model had no interpretability. High accuracy but computationally expensive, not optimized for mobile use.
[23]	Grad-CAM for rare diseases (vitiligo)	Focus on uncommon disorders, not applicable to a wide range of skin conditions.
[24]	MobileNetV2	Complex model architecture not tested for real-time use or on Papulosquamous data.

This study employed DermNetNZ publicly available data while resolving data unbalance together with image quality problems to develop their diagnostic and feature extraction systems. Utilization of image processing techniques to overcome limitations associated with feature selection and regional data focus observed in conventional methodologies. The use of contrast limited adaptive histogram equalization (CLAHE) produces better image quality followed by MobileNetV2 architecture. This work presents an optimized MobileNetV2 with depthwise separable convolutions and bottleneck layers for accurate, lightweight skin disease detection [16]. The Papulosquamous SkinSense App combines Grad-CAM based visual explanations with a chatbot, enabling real-time diagnosis of PS, LP, PR, and PRP. While effective on mobile devices, challenges remain due to variable image quality, emphasizing the need for robust, mobile-friendly AI solutions.

2. METHOD

This study covers four phases. This encompasses gathering and preprocessing data, designing and training models, integrating explainability, and deploying via a mobile-friendly application. The first step is preprocessing, which utilizes data augmentation methods; after that, 80% of the dataset is allocated for training and 20% for testing. The second step utilized a sophisticated CNN architecture [17], [18], while the third step includes carrying out the procedure on the prepared model. These four stages are illustrated in Figure 1. For the purpose of experimentation, 3120 images were chosen from the available open-source dataset [19]-[25]. Deep learning model was trained on 624 images, while the remaining 100 images served for validation. The CLAHE method was used to enhance the images. It is an abbreviation for the algorithm "contrast limited adaptive histogram equalization." MobileNetV2, InceptionV3, and NASNet pre-trained CNN models, along with hybrid architectures, are utilized for the categorization and detection of skin images.

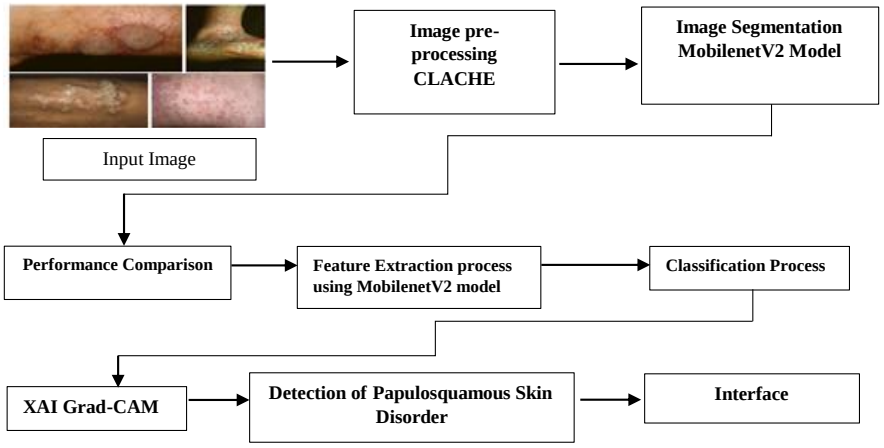

Figure 1. Proposed MobileNetV2 architecture with Grad-CAM

2.1. Data collection and processing

This research obtained 19,500 clinical images from DermNetZ and kaggle databases which contain pictures of 23 different skin conditions [20]-[25]. This classification system contains four classes: PS along with LP and PR as well as PRP with an equally distributed class quantity. The image processing included 3,120 pictures and followed training and testing data splits. The image collection includes JPEG files packed with RGB color channels but displays different resolutions per category type. Collect images dataset $X=\{x_1, x_2\ldots, x_n\}$, resize to 224×224×3, normalize X/255, and apply data augmentation techniques.

2.2. Class imbalance handling with synthetic minority over-sampling technique

A total of 3,120 dermoscopic images were processed, with 2,496 used for training and 624 for testing (80:20 split). Due to class imbalance in the training set, synthetic minority over-sampling technique (SMOTE) was applied only on the training data to generate synthetic samples for minority classes, while maintaining the overall size at 2,496 images (2496,224,224,3). To enhance contrast and improve feature extraction, CLAHE was applied prior to classification using MobileNetV2 for multi-class papulosquamous disease detection [21]:

$$G(CLAHe) = min(G\_eq(x,y), C\ , i \in \{0,1,2,3\}$$

Where, G(CLACHE) is the CLACHE processed histogram for the papulosqumous skin disease class (PS,PRP,PR,LP) . G_eq (X,Y) is the standard histogram equalization result for each class. C is the clip limit to prevent over enhancement. The processed images from CLAHE move to MobileNetV2 for feature extraction which leads to classification. The disease detection based on softmax function enables normalization of last-layer output into a probability distribution according to this: $P(y-c_i|x) = \frac{e^{zi}}{\sum_{j-1}^{N} e^{zi}}$. Where, $P(y-c_i|x), z_i, N$ are the probability of class c_i given input$x$, score for class c_i, respectively.

To ensure explainability, the model is complemented by interpretability techniques: Grad-CAM. Grad-CAM generates heatmaps highlighting the most influential regions in the image that contribute to the model's decision which is shown in Figure 2.

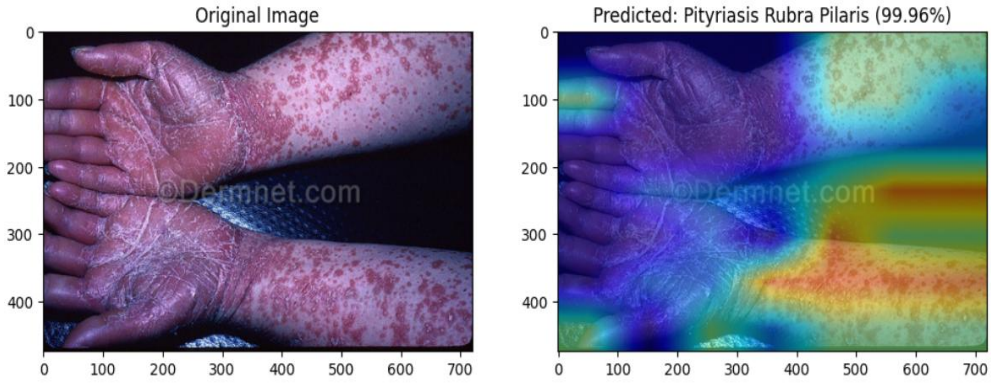

Figure 2. Visualizing model decisions with Grad-CAM

2.3. Model setup

Use MobileNetV2, for feature extraction: add global average pooling (GAP), fully connected layers, and Softmax function which is as:

$$y_i = \frac{e^{W2hi+b2}}{\sum_k e^{W2hi+b2}}$$

2.4. Training and optimization

The model was trained using transfer learning with ImageNet-initialized weights and augmented with random rotation, flipping, and zooming for better generalization. Training used the Adam optimizer (learning rate 0.001), categorical cross-entropy loss, batch size 32, and up to 100 epochs with early stopping to prevent overfitting.

$$Entropy\ loss: Loss = \sum_{i=1}^{N} y_i\ log\ (\hat{y}_i)$$

2.5. Explainability and performance

To enhance interpretability, Grad-CAM was used to generate heatmaps highlighting key lesion regions, improving clinical trust. Model performance was comprehensively assessed using accuracy, precision, recall, F1-score, and area under the curve–receiver operating characteristic (AUC-ROC), ensuring robust evaluation across classes.

$$Le_{GradCAM=}\text{ReLU}(\sum_k (w^e k A^k)$$

Enhance with CLAHE and overlay heatmaps and evaluate accuracy, precision, recall, and AUC-ROC curve.

2.6. Disease detection and deployment

The trained model was deployed within the Papulosquamous SkinSense App, featuring a Streamlit-based interface and TensorFlow/Keras backend. Users can upload skin images to obtain classification results with confidence scores alongside Grad-CAM visualizations. The app also integrates an LLM-driven chatbot that delivers personalized explanations and treatment guidance. Papulosquamous disease detection $\hat{y} = arg\ max\ f(x, \theta)$ and deploy in Papulosquamous Detection App.

2.7. Comparative performance of MobileNetV2, InceptionV3, NASNet, U-Net, and hybrid architectures

2.7.1. InceptionV3

It effectively identifies papulosquamous skin diseases by capturing both fine details, like scaling and subtle color changes, and broader lesion patterns, such as plaques and distribution. By applying 1×1, 3×3, and 5×5 convolutions. InceptionV3 provides powerful multi-scale feature representations, enhancing disease classification accuracy.

2.7.2. NASNet

It uses neural architecture search to automatically design optimal convolutional cells. Its stacked normal and reduction cells capture both local and global lesion patterns. In the hybrid model, NASNet adds efficient, hierarchical features that enhance robustness in skin disease classification.

2.7.3. U-Net

The model begins with a U-Net encoder that extracts hierarchical features from input skin images. The encoder consists of stacked convolutional layers with rectified linear unit (ReLU) activation, followed by max-pooling operations to progressively reduce spatial dimensions while increasing depth. This captures local lesion details and texture patterns critical for distinguishing papulosquamous skin diseases. The output of the encoder is then pooled globally to produce a compact feature vector.

2.7.4. Hybrid model (MobileNetV2+UNet+NASNet)

A hybrid model combining U-Net with pretrained MobileNetV2, InceptionV3, and NASNet was developed for dermoscopic image classification. Features from all networks were merged and passed through fully connected layers with dropout and batch normalization, ending in a SoftMax layer for classifying four skin diseases. Trained with the Adam optimizer, early stopping, and learning rate scheduling, the model achieved robust performance and was saved as unet_hybrid_skin_disease_model.h5, leveraging MobileNetV2's efficiency, InceptionV3's multi-scale extraction, and NASNet's optimized features for enhanced accuracy.

The performance metrics of the models present different numbers based on accuracy, precision, recall, and F1-score. The lightweight model, MobileNetV2, indicates moderate performance with 0.79 accuracy, as well as the precision, recall, and F1-score, all at 0.77. This shows to some extent balanced but lower performance compared to the other models. InceptionV3 performs considerably better, all the metrics are up to 0.91 meaning that it manages complicated data and produces balanced predictions. Further, NASNet outscores at 0.92 on all metrics with superior learning capacity and accuracy. The hybrid (MobileNetV2+U-Net) model, which uses MobileNetV2 and U-Net, yields consistent outputs at a 0.90 mark for all metrics and demonstrates its capability in performing segmentation task while still leading in terms of overall performance shown in Table 2. The hybrid (MobileNetV2+U-Net NASNet) model is slightly losing its performance the accuracy got down to 0.88, but the precision and recall are still good enough; the F1-score of 0.89 can be reached. Lastly, MobileNetV2+Grad-CAM gives the best results with an accuracy of 0.94 and precision, recall and F1-score of all 0.94 or higher. The introduction of Grad-CAM increases model interpretability and thus increases precision and recall since the decision-making process is more transparent, and there is best performance for the model which is shown in Figure 2.

Table 2. Comparison of the results with state of art

Model	Accuracy (related work) (%)	Proposed model accuracy (%)	Precision (proposed model) (%)	Recall (proposed model) (%)	F1-score (proposed model) (%)
MobileNetV2	88.9 [10]	0.79	0.77	0.77	0.77
NASNetMobile	0.91 [10]	0.92	0.92	0.92	0.92
IncepetionV3	0.911 [26]	0.91	0.91	0.91	0.91
U-Net	0.75 [27]	0.9	0.9	0.9	0.9
Hybrid (MobileNet V2+U-Net)	----	0.9	0.9	0.9	0.9
Hybrid (MobileNet V2+U-Net+NASNet)	----	0.88	0.89	0.88	0.89
Proposed MobileNetV2+Grad-CAM	0.93	0.94	0.95	0.94	0.94

3. RESULTS AND DISCUSSION

The models evaluated, MobileNetV2 enhanced with Grad-CAM stands out with the highest performance metrics achieving 94.23% accuracy, 94.74% precision, 94.23% recall, and an F1-score of 94.21%. These results surpass those of both standard MobileNetV2 and hybrid architectures like MobileNet+U-Net and MobileNet+NASNet. The implementation of Grad-CAM not only aids in model interpretability but also appears to enhance diagnostic reliability. This improvement is likely due to better feature localization and more informative gradient-based attention. Furthermore, the model's robustness is supported by AUC-ROC values close to or at 100% for all disease classes—98.42% for LP, 99.01% for PR, 100.00% for PRP, and 99.80% for PS indicating excellent discriminative capability. These findings confirm that MobileNetV2 combined with Grad-CAM not only achieves superior classification. This study evaluates MobileNetV2 with Grad-CAM regarding its robustness. Among all the evaluated models the proposed approach displayed superior performance in distinguishing four types of papulosquamous skin disease. The trained models operated for 50 and 100 epochs through implementation of transfer learning in combination with hyperparameter adjustment. The MobileNetV2 model trained for 100 epochs reached outstanding performance in diagnosing papulosquamous disorders by obtaining a 94.23% accuracy alongside precision of 94.74% and recall of 94.23% and an F1-score of 94.21%. The AUC-ROC curve shows that the model provides excellent disease class discrimination with 98.42% AUC for LP while PR achieved 99.01% and

PRP reached 100.00% and PS had 99.80%. The depth-wise separable convolutions within MobileNetV2 enable both efficient feature selection and high dermatological feature retention which led to its success. By using pretraining weights transfer learning allowed the model to extract important lesion characteristics that resulted in improved classification results. Learning rate scheduling combined with dropout and data augmentation that included rotation along with flipping and zooming led to better generalization and stopped the model from overfitting [22], [23]. Moreover, handling class imbalance it ensured that the model performed consistently across all disease categories performance but also maintains high generalization and reliability across all skin disease classes evaluated. Therefore, the model demonstrates high classification reliability because it produces nearly perfect scores indicating minimal false results among different skin condition diagnoses. Which is shown in Table 2 with state of art. The Papulosquamous SkinSense Detection App achieves correct classification of papulosquamous skin conditions through the integration of explainable AI and deep learning while providing interpretive results to users. The Streamlit-developed program implements a MobileNetV2 model that underwent training across 100 epochs to reach 96% accuracy [24], [25]. The models evaluated, MobileNetV2 enhanced with Grad-CAM stands out with the highest performance metrics achieving 94.23% accuracy, 94.74% precision, 94.23% recall, and an F1-score of 94.21%. These results surpass those of both standard MobileNetV2 and hybrid architectures like MobileNet V2+U-Net and MobileNetV2+NASNet [26].

The integration of Grad-CAM improves interpretability and diagnostic reliability by enhancing feature localization and gradient-based attention. The model also shows strong robustness, achieving near-perfect AUC-ROC scores 98.42% (LP), 99.01% (PR), and 100% (PRP), and 99.80% (PS) indicating excellent disease discrimination. These findings confirm that integrating MobileNetV2 with Grad-CAM delivers superior classification accuracy, strong generalization, and consistent reliability across all evaluated skin disease classes [27]. The Papulosquamous detection Web App integrates several essential libraries to ensure smooth AI-driven diagnosis and interpretation. NumPy manages numerical computations, while TensorFlow powers the MobileNetV2 model for disease identification. Streamlit provides an interactive web interface, and Pillow supports image processing. Temporary image handling is managed by the OS library, ensuring files are securely processed and deleted. Through the Google Generative AI platform (Gemini AI), the app generates customized precaution messages based on prediction confidence levels. Grad-CAM enhances transparency by visually highlighting key lesion regions, improving user understanding of the model's decisions. The system accurately classifies four papulosquamous diseases— PS, LP, PR, and PRP. Based on model confidence, the app offers tailored suggestions: urgent alerts for confidence above 80%, consultation advice between 50–80%, and basic skincare tips below 50%. Together, these components create an explainable, efficient, and patient-friendly diagnostic tool.

The application uses custom CSS for design purposes to deliver an attractive interface with easy navigation. The system handles file format checks before imaging normalization for predictions while creating two sections in the output, which shows the initial image and diagnostic results with scores and AI-generated risk advisories. The model exhibits robust discriminatory performance because its AUC-ROC scores have reached a perfect value of 100%. This shows its potential as a consistent clinical AI solution to detect skin diseases. The app unites MobileNetV2 with Grad-CAM and generative AI functionality to create a connection between automated skin diagnostics and patient education systems that improves usability alongside trust and transparency for clinic use. It demonstrates the feasibility of integrating image-based analysis with empathetic support, achieving promising outcomes despite limitations posed by a small dataset. Results are drawn from model testing on a limited test set and preliminary user interactions, highlighting both technical achievements and areas for future refinement, such as dataset diversity and handling of false detections. Other study reported classification results by attaining 94.76%, as demonstrated by, as reported by Srinivasu *et al*. [16] and Al-Masni *et al*. [26] and 85%.

Papulosquamous SkinSense detection app combines the great strength of deep learning with conversational AI to form a coherent solution for streamlining dermatological diagnostic processes. Using React-Vite, the front-end has offered an interface whereby users can upload clean photographs of their skin for analysis. After this, images are streamed to a FastAPI endpoint running beneath the control of Azure, which provides fast and scalable capabilities for processing. In the backend, at its core, is a hybrid MobileNetV2 model that has been highly fine-tuned and pre-trained for 100 times whilst specializing to recognize visual similarities between the papulosquamous skin conditions [27]. Following analysis, the user gets back the selected skin condition and confidence on that diagnosis. SkinSense accurately identified the skin state during the real-time demo as PRP (ACE with high confidence of 98.8%), and within a second, the analytics was shown on the dashboard along with the uploaded image. After receiving the prediction, the platform refreshes the frontend with clean and interactive rendering of the reported results. To make it easier for users to understand diagnosis, the system uses the Gemini API to provide specific instructions or regimen where appropriate depending on the kind of skin disorder detected. To this end, the AI assistant provides conversational help that answers the user's questions, defines complex medical words and pushes users to the

next best step in accordance with their diagnosis. Through the fusion of LLM-based support and interpretable AI, SkinSense maximizes diagnostic results as well as enhances user comfort and simplifiability in the environment of digital dermatology which is shown in Figure 3. The MobileNetV2 model enhanced with Grad-CAM showed superior performance in classifying four papulosquamous skin diseases PS, LP, PR, and PRP achieving 94.23% accuracy, 94.74% precision, 94.23% recall, and an F1-score of 94.21%, outperforming standard MobileNetV2 and hybrid architectures (Table 2). Class-wise AUC-ROC values confirmed robustness, reaching 98.42% for LP, 99.01% for PR, 100% for PRP, and 99.80% for PS. Grad-CAM improved interpretability by highlighting lesion regions (Figure 3), while transfer learning and data augmentation enhanced feature extraction and generalization. Compared to prior studies, the model significantly outperformed U-Net (75.3% [27]), MobileNetV2 alone (88.9% [10]), and NASNetMobile (91% [10]). Deployment through the Papulosquamous SkinSense Detection App allowed users to receive disease classification, confidence scores, Grad-CAM visualizations, and AI-based recommendations (Figures 2 and 3). The SkinSense system, though effective, has limitations such as a small dataset, evaluation of only four disease categories, and lack of external validation, which may affect generalizability. Future work should address these to enhance robustness. Despite this, the model shows strong accuracy, interpretability, and usability for automated skin disease detection. A key innovation is the Gemini-powered chatbot, fine-tuned on 50 dermatology texts to deliver empathetic, PS -focused advice. Using a structured prompt, it generates dynamic precaution messages based on prediction confidence ranging from immediate action to general care making the system both intelligent and user-centered.

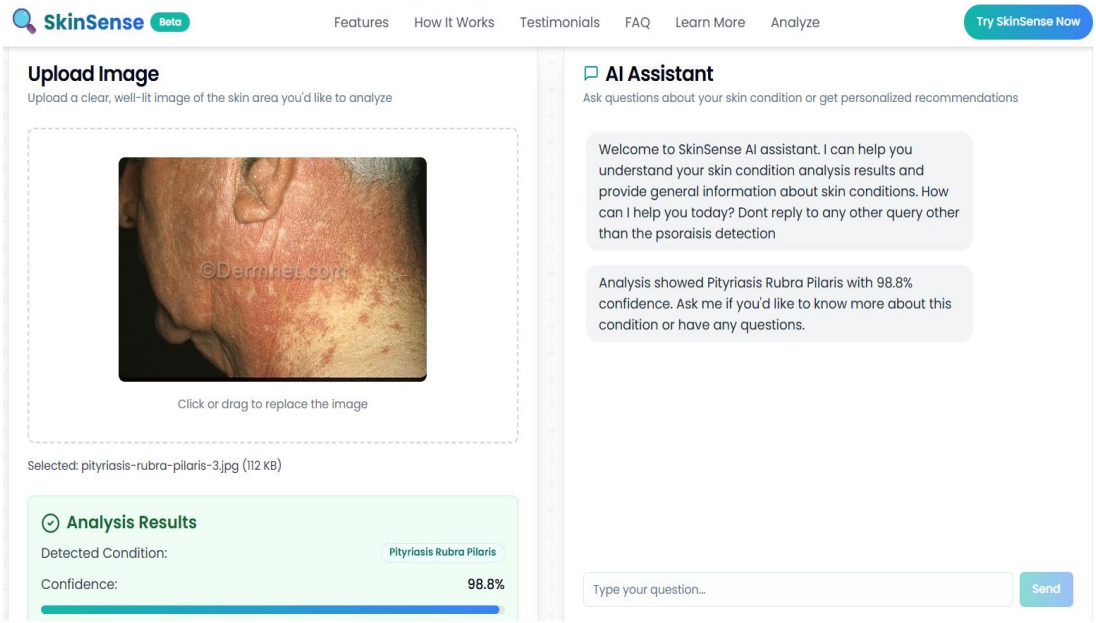

Figure 3. Papulosquamous SkinSense Detection App

4. CONCLUSION

This study demonstrates that MobileNetV2 enhanced with Grad-CAM provides highly accurate and interpretable classification of papulosquamous skin diseases PS, LP, PR, and PRP achieving 94% accuracy and 95% precision among MobileNetV2, InceptionV3, NASNet, and hybrid models. The SkinSense Detection App combines transfer learning, data balancing, and Grad-CAM visualizations into a robust, user-friendly diagnostic tool, supported by an LLM-powered chatbot for real-time personalized feedback. High performance metrics (98.08% overall success rate) and positive user ratings (4.6–4.8/5) confirm its clinical reliability and accessibility. While additional diverse data could reduce occasional false positives, this work illustrates the potential of explainable AI in dermatology, bridging technical accuracy with practical usability. These findings suggest broad applications in AI-assisted clinical practice and provide a foundation for extending the system to additional skin conditions, larger datasets, and enhanced patient interaction, contributing to more accurate, interpretable, and accessible skin disease diagnosis.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

All data supporting the findings of this study are included in the references.

REFERENCES

[1] G. Martin *et al*., "Pathological crosstalk *in vitro* between T lymphocytes and lesional keratinocytes in psoriasis: necessity of direct cell-to-cell contact," *Laboratory Investigation*, vol. 92, no. 7, pp. 1058–1070, 2012, doi: 10.1038/labinvest.2012.69.

[2] R. J. Hay *et al*., "The global burden of skin disease in 2010: an analysis of the prevalence and impact of skin conditions," *Journal of Investigative Dermatology*, vol. 134, no. 6, pp. 1527–1534, 2014, doi: 10.1038/jid.2013.446.

[3] H. Sung *et al*., "Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries," *CA: A Cancer Journal for Clinicians*, vol. 71, no. 3, pp. 209–249, 2021, doi: 10.3322/caac.21660.

[4] M. F. Akter, S. S. Sathi, S. Mitu, and M. O. Ullah, "Lifestyle and heritability effects on cancer in Bangladesh: an application of Cox proportional hazards model," *Asian Journal of Medical and Biological Research*, vol. 7, no. 1, pp. 82–89, 2021, doi: 10.3329/ajmbr.v7i1.53313.

[5] J. D. Khoury *et al*., "The 5th edition of the World Health Organization classification of haematolymphoid tumours: myeloid and histiocytic/dendritic neoplasms," *Leukemia*, vol. 36, no. 7, pp. 1703–1719, 2022, doi: 10.1038/s41375-022-01613-1.

[6] W. Roberts, "Air pollution and skin disorders," *International Journal of Women's Dermatology*, vol. 7, no. 1, pp. 91–97, 2021, doi: 10.1016/j.ijwd.2020.11.001.

[7] R. Mittal, F. Jeribi, R. J. Martin, V. Malik, S. J. Menachery, and J. Singh, "DermCDSM: Clinical Decision Support Model for Dermatosis Using Systematic Approaches of Machine Learning and Deep Learning," *IEEE Access*, vol. 12, pp. 47319-47337, 2024, doi: 10.1109/ACCESS.2024.3373539.

[8] R. Bhargava, "Clinico-pathological correlation of papulosquamous lesions of skin: an institutional study," *Journal of Advanced Medical and Dental Sciences Research*, vol. 8, no. 2, pp. 19–22, 2020, doi: 10.21276/jamdsr.

[9] S. Kohli, U. Verma, V. V. Kirpalani, and R. Srinath, "Dermatobot: An Image Processing Enabled Chatbot for Diagnosis and Tele-remedy of Skin Diseases," in *2022 3rd International Conference for Emerging Technology (INCET)*, Belgaum, India, 2022, pp. 1-5, doi: 10.1109/INCET54531.2022.9824756.

[10] I. Hestiningsih, A. N. A. Thohari, - Kurnianingsih, and N. D. Kamarudin, "Mobile Skin Disease Classification using MobileNetV2 and NASNetMobile," *International Journal on Advanced Science, Engineering & Information Technology*, vol. 13, no. 4, pp. 1472-1479, Jul. 2023, doi: 10.18517/ijaseit.13.4.18290.

[11] K. Varma, U. Kumar, and V. Kumar, "Clinical pattern of papulosquamous dermatoses: An observational study conducted at tertiary care center, Ujjain, Madhya Pradesh, India," *International Journal of Research in Dermatology*, vol. 6, no. 2, pp. 230–236, 2020, doi: 10.18203/issn.2455-4529.IntJResDermatol20200602.

[12] T. Guergueb and M. A. Akhloufi, "Melanoma Skin Cancer Detection Using Recent Deep Learning Models," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Nov. 2021, pp. 3074-3077, doi: 10.1109/embc46164.2021.9631047.

[13] A. Wibowo, C. A. Hartanto, and P. W. Wirawan, "Android skin cancer detection and classification based on MobileNet v2 model," *International Journal of Advances in Intelligent Informatics*, vol. 6, no. 2, p. 135, Jul. 2020, doi: 10.26555/ijain.v6i2.492.

[14] S. Dissaneevate *et al*., "A Mobile Computer-Aided Diagnosis of Neonatal Hyperbilirubinemia using Digital Image Processing and Machine Learning Techniques," *International Journal of Innovative Research and Scientific Studies*, vol. 5, no. 1, pp. 10-17, Jan. 2022, doi: 10.53894/ijirss.v5i1.334.

[15] R. Saifan and F. Jubair, "Six skin diseases classification using deep convolutional neural network," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 3, pp. 3072-3082, Jun. 2022, doi: 10.11591/ijece.v12i3.pp3072-3082.

[16] P. N. Srinivasu, J. G. SivaSai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM," *Sensors*, vol. 21, no. 8, pp. 1-27, Apr. 2021, doi: 10.3390/s21082852.
[17] P. Kaur, "Performance and Accuracy Enhancement During Skin Disease Detection in Deep Learning," *International Journal of Experimental Research and Review* (*IJERR)*, vol. 35, pp. 96-108, Nov. 2023, doi: 10.52756/ijerr.2023.v35spl.009.
[18] T. D. Nigat, T. M. Sitote, and B. M. Gedefaw, "Fungal Skin Disease Classification Using the Convolutional Neural Network," *Journal of Healthcare Engineering*, pp. 1-9, May 2023, 10.1155/2023/6370416.
[19] H. Yildirim *et al*., "An automated diabetic retinopathy disorders detection model based on pretrained MobileNetv2 and nested patch division using fundus images," *Journal of Health Sciences and Medicine*, vol. 5, no. 6, pp. 1741-1746, Oct. 2022, doi: 10.32322/jhsm.1184981.
[20] J. Zhou, Y. Li, and X. Guo, "Predicting psoriasis using routine laboratory tests with random forest," *PLOS ONE*, vol. 16, no. 10, p. e0258768, Oct. 2021, doi: 10.1371/journal.pone.0258768.
[21] M. N. Bajwa *et al.*, "Computer-aided diagnosis of skin diseases using deep neural networks," *Applied Sciences*, vol. 10, no. 7, pp. 1-13, Apr. 2020, doi: 10.3390/app10072488.
[22] K. Dhawale and A. R. P. Bhagat, "Hybrid VGG19 with Combined XGBoost Deep Neural Network for Improved Papulosquamous Skin Diseases Classification," *Advances in Nonlinear Variational Inequalities*, vol. 28, no. 6s, pp. 64-80, 2025, doi: 10.52783/anvi.v28.4122.
[23] F. Nunnari, M. A. Kadir, and D. Sonntag, "On the overlap between Grad-CAM saliency maps and explainable visual features in skin cancer images," in *International Cross-Domain Conference for Machine Learning and Knowledge Extraction*, 2021, pp. 241–253, doi: 10.1007/978-3-030-84060-0_16.
[24] G. J. Castelino, K. Chadaga, and N. Sampathila, "Explainable Deep Learning for Dermatology: Psoriasis vs. Eczema with Grad-CAM," in *2024 2nd International Conference on Recent Advances in Information Technology for Sustainable Development (ICRAIS)*, Manipal, India, 2024, pp. 194-199, doi: 10.1109/ICRAIS62903.2024.10811706.
[25] DermNet NZ.‖ website: dermnetnz.org, license: https://creativeco mmons.org/licenses/by-nc-nd/3.0/nz/legalcode. (Accessed Jun. 01, 2021).
[26] M. A. Al-Masni, D. Kim, and T. Kim, "Computer Methods and Programs in Biomedicine Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification," *Computer Methods and Programs in Biomedicine*., vol. 190, p. 105351, 2020, doi: 10.1016/j.cmpb.2020.105351.
[27] S. M. Al-Barzinji, N. Q. Abdulmajeed, A. S. Ahmed, and M. Al-Kubaisi, "Optimized deep learning for skin cancer diagnosis: A salp swarm-optimized MobileNetV2 approach with Grad-CAM interpretation," *Ingénierie des Systèmes d'Information*, vol. 30, no. 6, p. 1491, Jun. 2025, doi: 10.18280/isi.300608.

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