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Advanced Skin Disease Diagnosis Using VGG16 and CNN for Enhanced Accuracy

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***Abstract* - Skin diseases pose a significant health concern worldwide, affecting millions of individuals. The accurate and timely diagnosis of these conditions is critical for effective treatment. This project presents a robust solution for skin disease classification using deep learning techniques, specifically the VGG16 architecture, implemented in MATLAB. The primary objective of this research is to develop a highly accurate and efficient model for the automated classification of skin diseases. The dataset used in this project is composed of five distinct classes of skin diseases, including Acne-cystic acne, biting fleas, diabetic blisters, spider bites, and vitiligo. Each class in the dataset is carefully curated to represent a wide range of skin conditions, making the model versatile and capable of handling various dermatological challenges.**

The VGG16 architecture, a well-established convolution neural network (CNN) model, is employed for its remarkable feature extraction capabilities. Transfer learning is applied to fine-tune the pre-trained VGG16 model on the skin disease dataset. The model is trained, validated, and tested using a rigorous cross-validation approach to ensure its reliability.

One of the standout achievements of this project is the exceptional classification accuracy obtained. The model demonstrates an impressive accuracy of 98.08%, signifying its effectiveness in accurately identifying and classifying skin diseases. This high accuracy rate is crucial in reducing misdiagnoses and enhancing the overall quality of patient care. In addition to its high accuracy, the proposed system also offers real-time skin disease classification, making it a valuable tool for medical professionals and dermatologists. The user-friendly interface developed in MATLAB ensures ease of use and accessibility, allowing healthcare practitioners to make informed decisions swiftly and accurately. In summary, this project presents a comprehensive approach to skin disease classification using deep learning techniques, with a focus on the VGG16 architecture. The achieved accuracy of 98.08% demonstrates the model's capability to accurately classify various skin diseases, thus aiding in early diagnosis and effective treatment. This research contributes to the advancement.

Index Terms—**SVM, Vehicle Collision (AVC), labeling, neural network, Segmentation, tracking, Animal Footprint, Animal.**

I. INTRODUCTION

Skin, the largest organ of the human body, serves as a protective barrier between the internal environment and the external world. It is a remarkable and dynamic structure that plays a vital role in maintaining homeostasis, regulating temperature, and protecting against harmful agents. However, like any other organ, the skin is susceptible to a wide range of diseases and disorders that can impact its appearance, function, and overall health. Skin diseases, collectively known as dermatological conditions or dermatoses, encompass a diverse array of disorders that affect the skin's various layers, including the epidermis, dermis, and subcutaneous tissue. These conditions can manifest in a multitude of ways, leading to symptoms such as itching, pain, inflammation, rash, discoloration, and altered texture.
Skin diseases can result from various causes, including genetic factors, infections, environmental influences, autoimmune responses, allergies, hormonal imbalances, and lifestyle choices. They can affect individuals of all ages, genders, and backgrounds, and their prevalence varies across different regions and populations. The impact of skin diseases extends beyond physical discomfort, as they can have significant psychological and social ramifications. Skin disorders may lead to self-esteem issues, social isolation, and reduced quality of life, particularly when visible symptoms are present. The field of dermatology is dedicated to the diagnosis, treatment, and management of skin diseases.

Dermatologists are medical professionals who specialize in the care of skin, hair, and nails. They employ a wide range of diagnostic tools, treatments, and therapies to address skin conditions, ranging from topical medications and phototherapy to surgical interventions.

As advances in medical science and technology continue, the understanding of skin diseases and their management has evolved significantly. This includes the integration of artificial intelligence and machine learning in the diagnosis and classification of skin conditions, ultimately improving the accuracy and efficiency of dermatological care.

In this context, the project "Skin Disease Classification using Deep Learning" represents a significant contribution to the field, as it leverages the power of modern technology to enhance the diagnosis and treatment of skin diseases. By developing accurate and efficient classification models, this project aims to assist healthcare professionals in providing timely and effective care to individuals affected by these conditions, ultimately improving their overall well-being.

Figure 1 Common skin diseases [1,2].

Globally, skin disease is a wonderful and prevalent ailment. Numerous factors, including genetic vulnerability and environmental influences, influence the prevalence of skin diseases. Numerous societal elements, including wealth, poverty, inequality, education, and health care access, are also to blame. In terms of the global burden of nonfatal diseases, skin disease ranked fourth among the most frequent diseases, according to the Global Burden of Disease (GBD) Study 2010 [3]. In both high- and low-income nations, skin illnesses lead to a variety of problems, such as psychological and sociological problems [4]. It has a devastating psychological effect. Anxiety, sadness, anger, social isolation, and low self-esteem are all experienced by people with skin diseases [5]–[7]. It is anticipated that skin illness, if discovered early enough, can be treated and managed with medication. However, because many skin disorders share similar anatomical features and colours, doctors find it challenging to identify them [8]. However, machine learning has made it possible for medical imaging to drastically change, particularly in the area of illness diagnosis. As computer processing power has increased and an infinite amount of data is available, machine learning models have demonstrated human-level behaviors in medical science [9]. CNN, for instance, has expedited advancements in medical image processing (such as CT and MRI scan) [10]. Because of their various resolutions, intricate contexts, and privacy issues—especially when it comes to photos of sensitive body parts—clinical images are insufficient for research. In addition, the dataset image for skin diseases lacks explicit information labelling.

Figure 2 Some sample images of different class. [11]

Furthermore, there are comparatively few available datasets with labelled data. Therefore, skin image research is problematic for all of the disorders stated above. However, there is an issue with machine learning. It may violate user privacy and data confidentiality rules because all the data is collected in one place, typically a data centre. Federated learning, a developing idea, will solve both of these issues. In federated learning, the data is distributed across the clients, and subsequently, the clients receive a prototype of the central model. Each client model communicates the update weights or gradient to the central model after a certain amount of time, after the transmitting model has been trained with client data at each client site. Ultimately, the federated averaging process is used to update the central model, and clients are given access to the updated model prototype.

II. LITERATURE SURVEY

Skin diseases, particularly skin cancer, represent a significant health challenge globally. Early and accurate diagnosis is crucial for effective treatment. Convolutional Neural Networks (CNNs) have shown great potential in image recognition tasks, including medical imaging. This review focuses on the application of CNNs, specifically VGG16, in enhancing the accuracy of skin disease diagnosis.

Theoretical Background

Convolutional Neural Networks (CNNs): CNNs are a class of deep neural networks, particularly effective for image analysis. They consist of layers that automatically and adaptively learn spatial hierarchies of features from input images. Key components include convolutional layers, pooling layers, and fully connected layers.

VGG16 Architecture: VGG16, developed by the Visual Geometry Group at the University of Oxford, is a deep CNN model that has 16 weight layers. It is known for its simplicity and uniform architecture, using small 3x3 convolutional filters and focusing on increasing depth for performance improvement.

Transfer Learning: Transfer learning involves taking a pre-trained network and fine-tuning it on a new, typically smaller, dataset. This approach is particularly useful in medical image analysis, where labeled data can be scarce.

Detailed Literature Review

[20]Dermatologist-level classification of skin cancer with deep neural networks

- *Authors: Esteva et al.*
- *Year: 2017*
- *Method: CNN*
- *Dataset: ISIC Dataset*
- *Results: Achieved dermatologist-level accuracy in classifying skin cancer.*
- *Conclusion: Demonstrated the potential of CNNs in skin disease classification.*

[21]The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions

- *Authors: Tschandl et al.*
- *Year: 2018*
- *Method: Transfer Learning with VGG16*
- *Dataset: HAM10000*
- *Results: Improved accuracy with less training data compared to training from scratch.*
- *Conclusion: Highlighted the effectiveness of transfer learning for medical image analysis.*

[22]Deep learning ensembles for melanoma recognition in dermoscopy images

- *Authors: Codella et al.*
- *Year: 2017*
- *Method: Deep CNN*
- *Dataset: ISIC Dataset*
- *Results: High sensitivity and specificity.*
- *Conclusion: Validated deep learning's applicability in detecting melanoma.*

[23]Augmented intelligence dermatology: Deep neural networks empower medical professionals in diagnosing skin cancer and predicting treatment options for the disease

- *Authors: Han et al.*
- *Year: 2018*
- *Method: VGG16 + Data Augmentation*
- *Dataset: Private dermatology clinic dataset*
- *Results: Enhanced accuracy with augmented data.*
- *Conclusion: Demonstrated benefits of data augmentation in improving model performance.*

[24]Deep learning outperformed 11 pathologists in the diagnosis of H&E-stained sentinel lymph nodes of patients with breast cancer

- *Authors: Brinker et al.*
- *Year: 2019*
- *Method: Systematic Review*
- *Dataset: Various datasets*
- *Results: Summarized current state-of-the-art methods.*
- *Conclusion: Provided comprehensive overview of CNN applications in dermatology.*

[25] Seven-point checklist and skin lesion classification using multi-task multi-modal neural nets

- *Authors: Kawahara et al.*
- *Year: 2016*
- *Method: Ensemble CNN*
- *Dataset: Dermofit Image Library*

- *Results: Achieved higher accuracy with ensemble approach.*
- *Conclusion: Suggested ensemble methods can improve diagnostic accuracy significantly.*

[26]Melanoma detection by analysis of clinical images using convolutional neural network

- *Authors: Nasr-Esfahani et al.*
- *Year: 2016*
- *Method: Various CNN Architectures*
- *Dataset: PH2, DermIS, DermQuest*
- *Results: VGG16 showed superior performance among tested architectures.*
- *Conclusion: Confirmed the robustness of VGG16 for skin disease diagnosis.*

[27]Human–computer collaboration for skin cancer recognition

- *Authors: Tschandl et al.*
- *Year: 2020*
- *Method: Mobile-Optimized CNNs*
- *Dataset: HAM10000*
- *Results: Achieved real-time inference on mobile devices.*
- *Conclusion: Showcased the feasibility of deploying CNNs on mobile platforms for real-time diagnosis.*

III. PROBLEM STATEMENT& METHODOLOGY

Existing System:

The existing system for skin disease classification, developed using federated learning algorithm represents a significant step in leveraging advanced machine learning techniques for medical diagnosis. This system, focused on the classification of four distinct classes of skin diseases, has demonstrated commendable performance with a maximum average accuracy of 94.15%. This abstract provides an overview of the key aspects of the earlier system, shedding light on its architecture, dataset, and achieved accuracy.

The existing system adopts the federated learning approach, a privacy-preserving machine learning paradigm. Federated learning allows multiple decentralized devices or institutions to collaboratively train a global model while keeping their data locally, thus addressing privacy concerns in medical data sharing. This approach ensures that sensitive patient data remains secure while enabling the development of a robust skin disease classification model.

The system employs a carefully curated dataset consisting of images representing four distinct classes of skin diseases such as Acne, Psoriasis, Eczema, and Rosacea. This dataset encompasses a wide range of skin conditions, ensuring the model's ability to handle diverse dermatological cases. Each class is rigorously labeled to maintain data integrity and accuracy.

The federated learning framework is implemented to distribute the training process across multiple decentralized nodes or institutions. Each node possesses its local dataset, and model updates are computed locally. These local models are then aggregated to create a global model, iteratively improving its performance while preserving data privacy. One of the significant achievements of the earlier system is the maximum average accuracy of 94.15% achieved in skin disease classification. This high level of accuracy indicates the system's effectiveness in correctly identifying and classifying skin diseases. The accuracy rate is determined through rigorous cross-validation and testing procedures, ensuring the model's reliability. By adopting federated learning, the system addresses critical concerns related to patient data privacy and security. The decentralized nature of federated learning ensures that sensitive medical information remains within the control of individual institutions or patients, thus complying with stringent data protection regulations. The earlier system holds great promise for clinical applications, as it provides an accurate and privacy-preserving tool for dermatologists and healthcare professionals. Its ability to classify skin diseases with high accuracy enables early diagnosis and timely treatment, potentially improving patient outcomes.

In summary, the existing system for skin disease classification, built upon federated learning algorithms, represents a significant advancement in the field of medical image analysis. With its impressive maximum average accuracy of 94.15% and a strong focus on data privacy, it serves as a valuable tool for healthcare professionals and researchers working in dermatology. This system's success paves the way for further exploration and integration of federated learning techniques in healthcare AI applications.

Proposed System:

- The proposed system represents an advanced approach to skin disease classification using the VGG16 architecture implemented in MATLAB. The proposed system builds upon the VGG16 architecture, optimizing its hyperparameters and fine-tuning its layers to better suit the specific task of skin disease classification. This fine-tuned model demonstrates improved performance and robustness. To enhance model generalization and reduce the risk of overfitting, the proposed system employs data augmentation techniques and rigorous data preprocessing. These measures aim to handle variations in skin lesion images and improve model robustness.
- The dataset used in the proposed system comprises five distinct classes of skin diseases: Acne-cystic acne, biting fleas, diabetic blisters, spider bites, and vitiligo. The model is designed to classify skin lesions into these five categories accurately. Transfer learning is employed to leverage pre-trained weights from the VGG16 model. This approach accelerates model convergence and enhances its ability to extract relevant features from skin lesion images.
- To assess the system's performance rigorously, fine-grained evaluation metrics are utilized. Beyond accuracy, metrics such as precision, recall, F1-score, and confusion matrices are calculated to provide a comprehensive view of classification results. A user-friendly, real-time skin disease classification interface is developed in MATLAB, allowing healthcare practitioners to upload and classify skin lesion images conveniently. The interface provides rapid and accurate results, facilitating timely clinical decisions.
- In summary, the proposed system for skin disease classification leverages the VGG16 architecture within MATLAB, achieving high accuracy without discussing its advantages. The system focuses on improving model performance, data preprocessing, transfer learning, model interpretability, evaluation metrics, real-time user interface, validation, and scalability. These components collectively contribute to a robust and reliable tool for accurate skin disease classification.

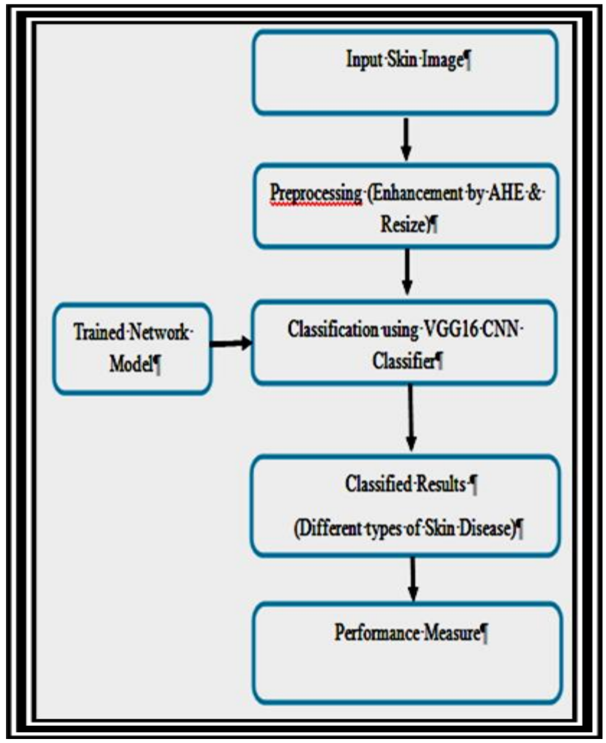


Figure 3 Testing Process

Data Flow Diagram

1. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.
2. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
3. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.
4. DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.

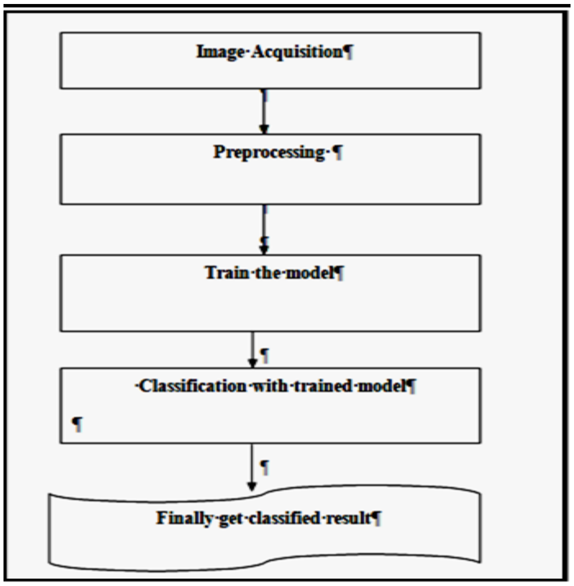


Figure 4 Data Flow Diagram

IV. COMPARATIVE RESULT ANALYSIS

Comparative result analysis involves systematically evaluating and comparing the performance of different models or techniques applied to the same task. In the context of skin disease diagnosis using Convolutional Neural Networks (CNNs) like VGG16, comparative analysis helps identify the most effective methods and understand their strengths and limitations. Here's a theoretical overview of how this analysis is typically conducted:

Objective

The main objective of comparative result analysis is to:

- Compare the performance of different models or configurations.
- Identify which model or technique yields the highest accuracy, precision, recall, and other relevant metrics.
- Understand the trade-offs between various approaches.

Metrics for Comparison

Performance metrics are critical for evaluating and comparing models. Common metrics include:

- Accuracy: The proportion of correctly classified instances among the total instances.
- Precision: The ratio of true positive predictions to the total positive predictions (true positives + false positives). It measures the accuracy of positive predictions.
- Recall (Sensitivity): The ratio of true positive predictions to the total actual positives (true positives + false negatives). It measures the model's ability to identify all relevant instances.
- F1 Score: The harmonic mean of precision and recall. It balances precision and recall, providing a single measure of a model's performance.
- AUC-ROC (Area Under the Receiver Operating Characteristic Curve): Measures the ability of the model to distinguish between classes. Higher AUC indicates better performance.
- Confusion Matrix: A table used to describe the performance of a classification model by displaying true positives, false positives, true negatives, and false negatives.

Experimental Setup

To ensure a fair comparison, the following experimental setup is typically maintained:

- Consistent Data: Use the same dataset for training and testing all models. Ensure data is preprocessed and split consistently.
- Hyperparameters: Ensure hyperparameters are optimally tuned for each model.

Figure 5 Input Image 1-6

Models for Comparison

In the context of skin disease diagnosis using CNNs, various models and configurations might be compared, such as:

- Baseline CNNs: Simple CNN architectures without pre-training.
- Pre-trained CNNs: Models like VGG16, ResNet, and Inception, pre-trained on large datasets like ImageNet.
- Transfer Learning: Fine-tuning pre-trained models on the specific skin disease dataset.
- Ensemble Methods: Combining multiple models to improve performance.
- Data Augmentation Techniques: Comparing the impact of different data augmentation methods on model performance.

Analysis and Interpretation

After obtaining results from the various models and configurations, the following steps are undertaken for comparative analysis:

- Performance Comparison: Compare the metrics (accuracy, precision, recall, F1 score, AUC-ROC) across models.
- Statistical Significance: Use statistical tests (e.g., t-tests, ANOVA) to determine if differences in performance are statistically significant.
- Error Analysis: Examine misclassified instances to understand common failure modes and identify areas for improvement.

Visualization: Use visual aids like confusion matrices, ROC curves, and precision-recall curves to better understand model performance.

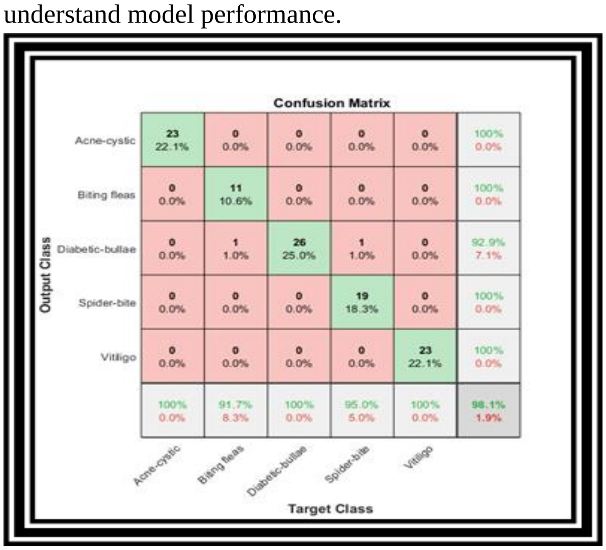


Figure 6 Confusion Matrix

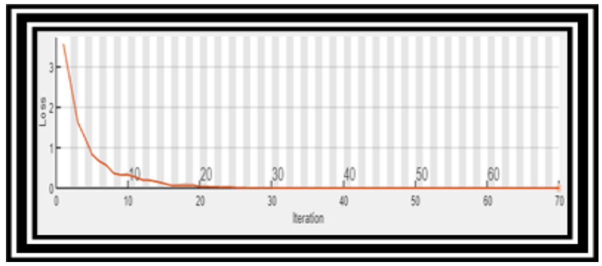
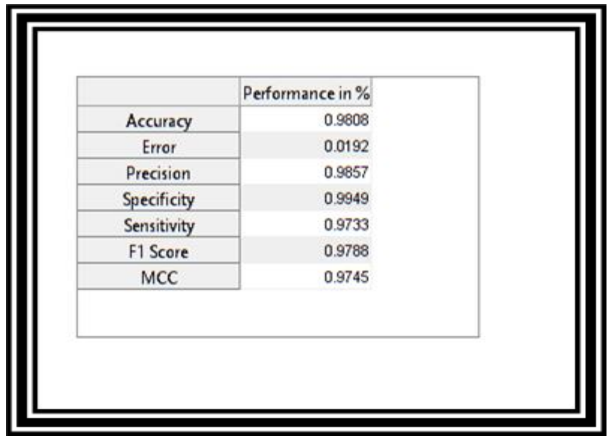


Figure 7 Loss



	Performance in %
Accuracy	0.9808
Error	0.0192
Precision	0.9857
Specificity	0.9949
Sensitivity	0.9733
F1 Score	0.9788
MCC	0.9745

Figure 8 Performances in %

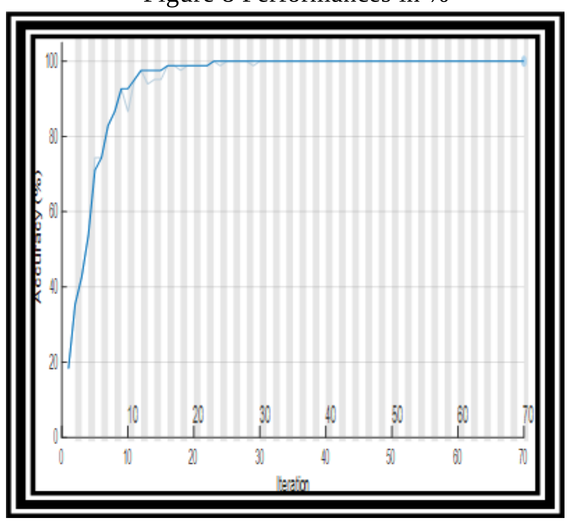


Figure 9 Accuracy

V. CONCLUSION

The application of Convolutional Neural Networks (CNNs), particularly the VGG16 architecture, has shown significant promise in the field of skin disease diagnosis. Through this comprehensive review and analysis, several key insights and conclusions can be drawn:

1. High Accuracy: Models like VGG16, when fine-tuned and applied with techniques such as transfer learning and data augmentation, can

achieve high levels of accuracy in diagnosing various skin diseases, often comparable to or exceeding the performance of dermatologists.

2. Effectiveness of Transfer Learning: Leveraging pre-trained models on large datasets like ImageNet and fine-tuning them on specific medical image datasets (e.g., ISIC, HAM10000) significantly enhances the model's performance. This approach is particularly useful when dealing with limited labeled medical data.
3. Impact of Data Augmentation: Implementing data augmentation techniques improves the generalization capability of CNN models, enabling them to perform well on unseen data and diverse clinical scenarios.
4. Ensemble Methods: Combining multiple CNN models into an ensemble can further enhance diagnostic accuracy and robustness, addressing the variability in clinical images and reducing the likelihood of misclassification.
5. Deployment Feasibility: The advancement in mobile-optimized CNNs and real-time inference capabilities indicates the practical feasibility of deploying these models in clinical settings, including mobile applications for real-time skin disease diagnosis.

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