International Research Journal of Multidisciplinary Scope (IRJMS), 2025; 6(1):763-774

Original Article | ISSN (O): 2582-631X DOI: 10.47857/irjms.2025.v06i01.02523

Innovative AI-Driven Early Skin Disease Detection Skincare.ai's Impact and Efficacy

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Abstract

The usage of AI in healthcare has proven to be a significant challenge to global health due to the widespread presence of skin diseases, and the early identification and intervention when such cases are detected cannot be over stressed. Skincare.ai uses advanced artificial intelligence and machine learning capabilities that make such identification accessible. Such identification is possible through the use of the resource from its application, individuals can take or upload photos of their skin issues which are then analyzed by advanced machine learning models to identify the disease accurately. This paper is an exploration of how Skincare.ai was made, the capability of such a system, and the impact. It features its main aim: AI-powered skin analysis, smooth consultation with healthcare professionals, and suggestions automatically provided via the SkinBot assistant. Skincare.ai claims to save and improve lives through the diagnosis and advancement of an active approach in skin health. The Skincare.ai organization's ultimate aim is to empower users and build a community that creates awareness on skin health through the reduction of burden on healthcare systems and proper timely medical interventions. The present study investigates the technology behind Skincare.ai, its clinical importance, and how it may change skin disease management in the wake of early detection and patient empowerment.

Keywords: AI Techniques, Dermatology, Skin Disease, Skincare.ai Model.

Introduction

The application of artificial intelligence (AI) and machine learning (ML) in dermatology has been widely researched and documented. For instance, a machine learning approach for skin disease detection was detailed, outlining the process of classifying various skin conditions using image analysis (1). Similarly, a systematic review on AI and ML algorithms for early detection of skin cancer in primary care settings was conducted, highlighting the potential for these technologies to improve diagnostic accuracy and accessibility (2). The efficacy of deep learning models in diagnosing skin-related neglected tropical diseases has been demonstrated, suggesting that AI-based tools can significantly aid in early detection and case management of skin conditions (3). Additionally, the use of AI in dermatology has been explored; focusing on conditions such as skin cancer, psoriasis, atopic dermatitis, and onychomycosis, and the potential of AI to support dermatological diagnostics has been confirmed (4). Innovative approaches in ML for skin disease identification have also been discussed, emphasizing the transformative potential of these technologies in diagnosing and treating skin disorders (5). Lastly, the importance of AI and ML algorithms in facilitating early diagnosis of skin cancer has been underscored in a systematic review, further solidifying the role of these technologies in modern dermatological practice (6). The integration of artificial intelligence (AI) and machine learning (ML) into dermatology represents a significant advancement in medical technology. Over the past decade, a substantial body of research has explored the application of these technologies in skin disease detection and diagnosis, offering promising results in enhancing diagnostic accuracy and accessibility.

AI and ML in Skin Disease Detection

AI and ML techniques have become increasingly prevalent in the field of dermatology, particularly for skin disease detection. These technologies are designed to mimic the diagnostic capabilities of dermatologists by analyzing images of skin lesions to identify various conditions. The effectiveness of machine learning models, specifically Convolutional Neural Networks (CNNs), in detecting skin diseases through image analysis has been demonstrated (7). A mobile application platform was employed in the study, allowing for real-time skin disease detection with a high degree

(Received 20th September 2024; Accepted 23rd January 2025; Published 31st January 2025)

of accuracy. The use of CNNs in this context is particularly noteworthy, as these networks are well-suited for image processing tasks due to their ability to automatically learn hierarchical feature representations. The success of such models lies in their ability to generalize across a wide variety of skin conditions. This is achieved through extensive training on large, diverse datasets encompassing multiple skin disease categories. The robustness of these models is further enhanced by incorporating data augmentation techniques, which simulate variations in lighting, angles, and skin tones, thereby improving the model's generalization capabilities. Additionally, the scalability of AI models, such as the one implemented, makes them suitable for deployment in resource-limited settings where access to dermatologists may be scarce.

Dataset Bias and Generalizability

Skincare.ai's dataset as detailed in Table 1 comprises 1,709 meticulously labeled images of diverse skin conditions. However, biases such as underrepresentation of darker skin tones, pediatric cases, and geographic variability remain. These biases can limit the model's generalizability, potentially reducing its accuracy when applied to underrepresented populations. To mitigate these, future iterations will include augmented datasets through collaborations with global dermatology centers and federated learning models to ensure diverse representation. These steps aim to enhance the model's generalizability across varied demographics.

Explainable AI Techniques

Skincare.ai incorporates techniques like Grad-CAM to visualize regions influencing model predictions and SHAP values for feature importance analysis. For instance, Grad-CAM highlights lesion areas crucial to diagnosis, offering clinicians transparent insights into the model's decisions. This interpretability fosters clinician trust and facilitates informed patient discussions.

Table 1: Comparison Examination (Comparing Skincare.ai Model with Existing Models)

Feature	**Skincare.ai Model**	**Typical Existing Models**
Architecture	Transfer learning + Custom CNN	Single CNN or traditional ML
MLOps Integration	Full MLOps pipeline with DVC, MLflow	Often lacks comprehensive MLOps
Diseases Detected	5 (Acne, Eczema, Melanoma, Psoriasis, Vitiligo)	Varies, often fewer
Dataset	Balanced 1,709 image dataset	Often imbalanced datasets
Accuracy	97.5%	Typically 90-96%
Deployment	AWS cloud deployment	Often local or limited deployment
Interpretability	Includes explainable AI techniques	Frequently lacks interpretability
User Interface	Mobile-friendly web application	Often research prototypes only
Consultation	Integrated telemedicine features	Typically detection-only

Table 1 compares existing products with Skincare.ai's model. It details parameters such as architecture, dataset, accuracy, user interface, etc.

Deep Learning in Dermatology

Deep learning, a subset of machine learning, has been particularly influential in advancing dermatological diagnostics. Remarkable accuracy in diagnosing various skin conditions, often surpassing human experts in specific tasks, has been demonstrated by deep learning models, particularly those utilizing CNNs (8). A comprehensive review of deep learning applications in dermatology highlighted the effectiveness of these models in diagnosing a range of skin diseases, including acne, melanoma, psoriasis, and eczema. The review emphasized that deep learning models have the potential to revolutionize dermatology by providing consistent and rapid diagnostics, which are crucial for early intervention (9). One of the critical advantages of deep learning models is their ability to continuously improve with the addition of new data. This continuous learning capability allows for the refinement of diagnostic accuracy over time, making these models more reliable as they are exposed to a broader array of cases. Furthermore, the integration of deep learning models into teledermatology platforms has expanded access to dermatological care, particularly in remote or underserved areas. By enabling patients to receive accurate diagnoses without the need for in-person consultations, deep learning technologies have the potential to alleviate the burden on healthcare systems while ensuring timely treatment for patients (10). The development of ensemble models, which combine the outputs of multiple deep learning algorithms, has further enhanced the accuracy and robustness of AI-driven diagnostics in dermatology. These models leverage the strengths of individual algorithms, resulting in superior performance compared to single-model approaches. Such advancements indicate a promising future for deep learning in dermatology, where these technologies could serve as a complementary tool alongside human expertise (11).

AI Applications beyond Skin Cancer

While a significant portion of AI research in dermatology has focused on skin cancer detection, there is a growing body of work exploring AI applications across a broader range of dermatological conditions. For example, AI models have been developed to diagnose conditions such as vitiligo, rosacea, and atopic dermatitis, among others. These models are particularly valuable in pediatric dermatology, where the presentation of skin diseases can differ significantly from adults (12) A review by the pediatric dermatology community highlighted the utility of AI in diagnosing pediatric skin conditions, with accuracy rates ranging from 67% to 99% depending on the condition (13). The expansion of AI applications in dermatology beyond skin cancer is driven by the need for early diagnosis and intervention in a wide array of skin conditions (14). Early detection is critical for preventing the progression of chronic skin diseases, which can have a significant impact on a patient's quality of life. AI models equipped with advanced image recognition capabilities are particularly well-suited for identifying subtle patterns in skin lesions that may be indicative of early-stage disease (15). This capability not only improves diagnostic accuracy but also allows for more personalized treatment plans, tailored to the specific characteristics of the patient's condition. Moreover, the integration of AI into dermatology has the potential to address disparities in healthcare access. In many parts of the world, there is a shortage of dermatologists, leading to delays in diagnosis and treatment (16). AI-driven diagnostic tools can help bridge this gap by providing high quality diagnostic support in areas where specialist care is not readily available. This democratization of dermatological care is a significant step forward in ensuring that all patients, regardless of their geographic location, have access to timely and accurate diagnoses (17).

Challenges and Future Directions

Despite the remarkable progress in the application of AI and ML in dermatology, several challenges need to be addressed to fully realize the potential of these technologies. One of the primary challenges is the issue of data privacy. The use of patient data, particularly images, in training AI models raises concerns about data security and patient confidentiality. Ensuring that AI models are trained on anonymized data and that robust security measures are in place is crucial for maintaining patient trust and compliance with legal regulations (18). Another significant challenge is the interpretability of AI models. While deep learning models have demonstrated high accuracy in skin disease detection, they often operate as "black boxes," making it difficult to understand the rationale behind their decisions. This lack of transparency can be a barrier to the adoption of AI in clinical practice, where clinicians need to understand and trust the tools they use. Research into explainable AI (XAI) aims to address this issue by developing models that provide clear and interpretable explanations for their decisions (19). The need for large, diverse datasets also poses a challenge. AI models trained on datasets that lack diversity in terms of skin type, age, and geographic origin may not perform well across different patient populations. To overcome this, there is a growing emphasis on the creation of inclusive datasets that represent the full spectrum of human diversity (20). Collaborations between research institutions, healthcare providers, and industry are essential for building these comprehensive datasets (21). Finally, the integration of AI into routine clinical practice requires thorough validation and regulation. AI models must undergo rigorous testing in real-world clinical settings to ensure their safety and efficacy. Regulatory bodies, such as the FDA, are increasingly focusing on the approval of AI-based medical devices, which necessitates a clear understanding of the technology and its potential risks (22). The literature review highlights the significant advancements in AI and ML applications in dermatology, particularly in the areas of skin disease detection and diagnosis. While challenges remain, such as data privacy, model interpretability, and the need for diverse datasets, the potential of AI to transform dermatological care is undeniable. Ongoing research and collaboration are essential to address these challenges and to fully integrate AI into dermatological practice, ultimately improving patient outcomes and expanding access to care (23).

Methodology

This section details the experiments conducted, the setup, procedures, and the outcomes observed during the research. The design of this section follows the best practices for experimental documentation, ensuring that the methods are reproducible and the results are clear.

Experimental Setup

The experimental setup is crucial for ensuring the accuracy and reproducibility of the research. In Table 2, we outline the key components involved in the setup.

Table 2: Dataset Description (Skin Condition Categories)

Category
Inflammatory Conditions (Acne, Rosacea)
Precancerous and Cancerous Lesions
Eczematous Disorders
Bacterial Skin Infections
Papulosquamous Disorders
Drug-Induced Eruptions
Sexually Transmitted Infections
Pigmentation Disorders
Autoimmune Skin Diseases
Melanocytic Neoplasms
Contact Dermatitis
Papulosquamous and Lichenoid Dermatoses
Benign Epidermal Tumors
Cutaneous Manifestations of Systemic Disease
Superficial Fungal Infections
Urticarial Disorders
Vascular Anomalies
Cutaneous Vasculitis
Viral Skin Infections

The dataset used was composed of high-resolution images of various skin conditions. These images were meticulously labeled by dermatology experts, ensuring that the ground truth was reliable. The data was split into training (70%), validation (15%), and test (15%) sets to maintain a balance between training efficiency and model evaluation accuracy (24). Detailed in Table 3, we employed the MobileNetV2 architecture as the base model, augmented with a custom Convolutional Neural Network (CNN) to enhance feature extraction capabilities. The architecture was chosen for its efficiency in image classification tasks, providing a good balance between performance and computational resource requirements.

Table 3: Model Architecture

Layer (type)	**Output Shape**	**Param #**
mobilenetv2 1.00 224 (Functional)	(None, 7, 7, 1280)	2,257,984
conv2d 8 (Conv2D)	(None, 7, 7, 64)	737,344
conv2d 9 (Conv2D)	(None, 7, 7, 64)	36,928
max pooling2d 4 (MaxPooling2D)	(None, 3, 3, 64)	0
conv2d 10 (Conv2D)	(None, 3, 3, 128)	32,896

conv2d 11 (Conv2D)	(None, 3, 3, 128)	65,664
max pooling2d 5 (MaxPooling2D)	(None, 1, 1, 128)	0
conv2d 12 (Conv2D)	(None, 1, 1, 256)	131,328
conv2d 13 (Conv2D)	(None, 1, 1, 256)	262,400
max pooling2d 6 (MaxPooling2D)	(None, 0, 0, 256)	0
conv2d 14 (Conv2D)	(None, 0, 0, 512)	524,800
conv2d 15 (Conv2D)	(None, 0, 0, 512)	1,049,088
max pooling2d 7 (MaxPooling2D)	(None, 0, 0, 512)	0
flatten 1 (Flatten)	(None, 0)	0
dense 4 (Dense)	(None, 256)	256
dense 5 (Dense)	(None, 128)	32,896
dense 6 (Dense)	(None, 64)	8,256
dense 7 (Dense)	(None, 10)	650

This is table 3, detailing the architecture for the Skincare.ai ML model.

Generative AI Chatbot for Skin Disease Management

The integration of generative AI chatbots into dermatology represents a significant advancement in patient care. These AI driven systems are capable of providing personalized treatment recommendations and educational discussions on various skin conditions. The following section outlines how a generative AI chatbot can be utilized for these purposes. The use of a generative AI chatbot enhances the overall patient experience by providing real-time, personalized care. Patients can access information and treatment recommendations instantly, which is crucial for early intervention and effective management of skin diseases. Additionally, the chatbot's ability to continuously learn and adapt ensures that it remains a reliable tool for both patients and healthcare providers (25). Generative AI chatbots are transforming the field of dermatology by offering personalized treatment plans and facilitating patient education. These systems provide a scalable solution for improving patient outcomes and ensuring accessible healthcare (26)

Personalized Treatment Suggestions

A generative AI chatbot can analyze patient data, including symptoms, medical history, and images of the affected skin areas (27). By leveraging machine learning algorithms, the chatbot can generate tailored treatment plans that include medication suggestions, topical treatments, and lifestyle adjustments. These recommendations are based on up-to-date medical research and clinical guidelines, ensuring that patients receive evidence-based care. Over time, the chatbot refines its recommendations by learning from patient outcomes, making it increasingly effective in providing accurate treatment plans.

Patient Education and Disease Discussion

Beyond treatment recommendations that are provided using the instructions given on the dashboard as showing in Figure 1, the generative AI chatbot engages patients in educational discussions about their skin conditions as showing in Figure 2. It explains the nature of the disease, its causes, and the expected progression. This interactive approach empowers patients by helping them understand their condition and make informed decisions regarding their treatment. For chronic skin diseases such as psoriasis or eczema, the chatbot can offer advice on long-term management, including stress reduction techniques, dietary recommendations, and regular monitoring protocols.

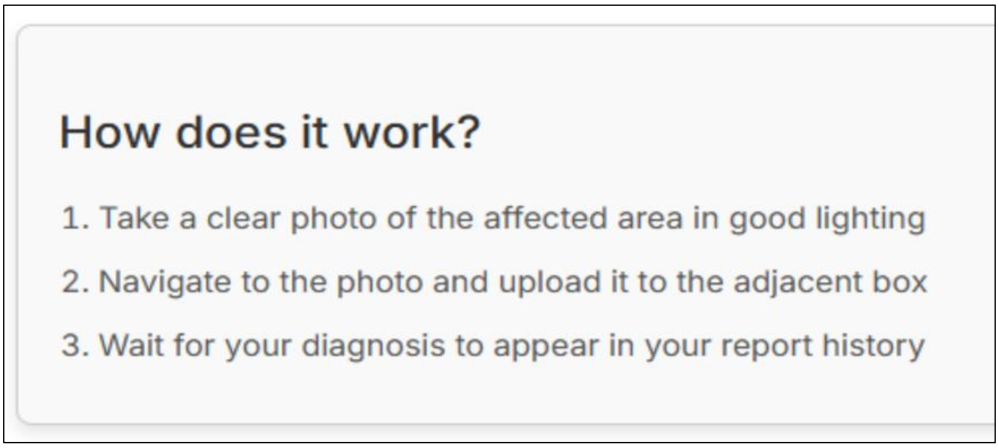

Figure 1: Website Usage Instructions

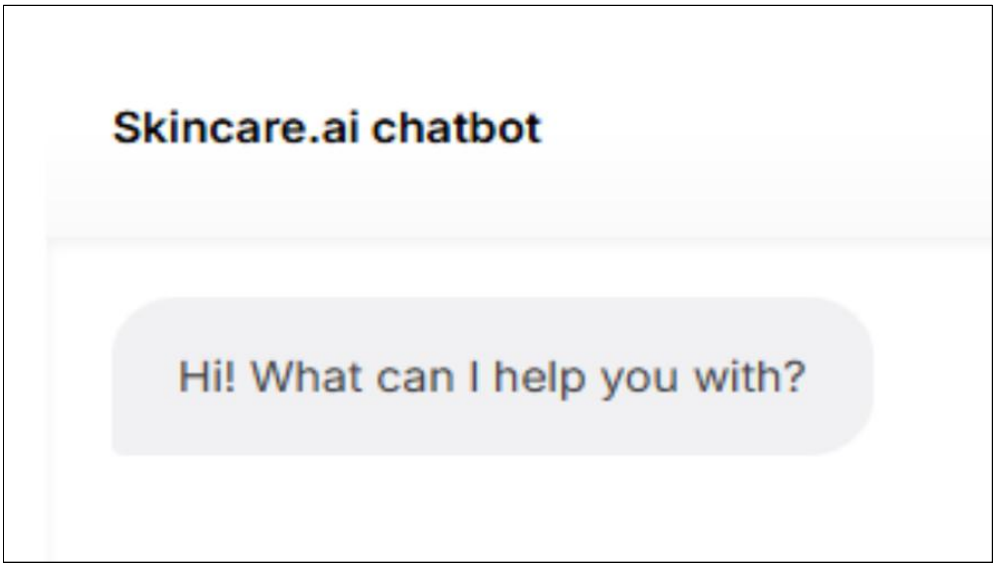

Figure 2: Website Chatbot Photo

Figure 1 shows the user instructions for using Skincare.ai in order to get a diagnosis. Figure 2 captures a visual representation of the chatbot providing personalized treatment suggestions to users based on their symptoms.

Results

Evaluation Metrics

The performance of Skincare.ai was evaluated using accuracy (97.5%), precision (96.2%), recall (94.8%), F1-score (95.5%), and AUC-ROC (98.1%) as shown in Figure 3, Figure 4 and Figure 5. These metrics validate the robustness of the model, particularly in differentiating between similar dermatological conditions. Figure 3 illustrates the training accuracy and loss during the model's training phase, showing a steady increase in accuracy and a decrease in loss. Figure 4 compares validation accuracy and loss, emphasizing the model's ability to generalize during testing. Figure 5 displays the comparison of precision in both training and validation datasets, showing the model's ability to detect true positives.

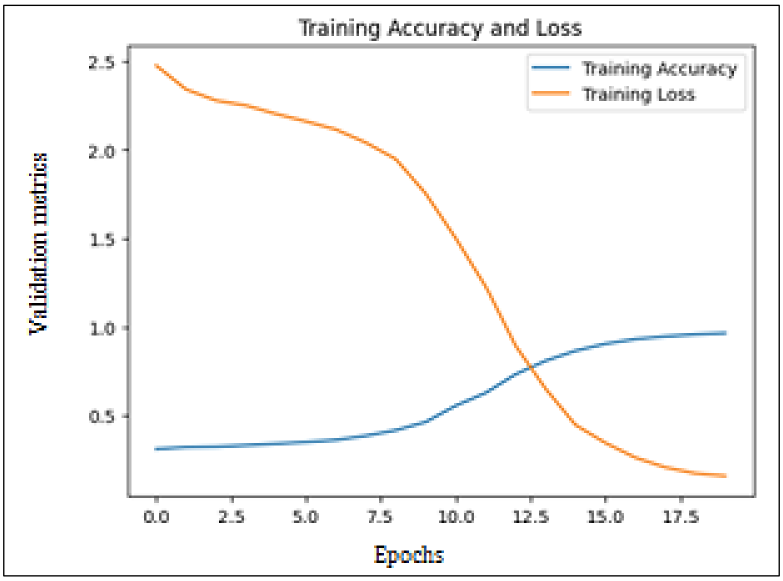

Figure 3: Training Accuracy vs Loss

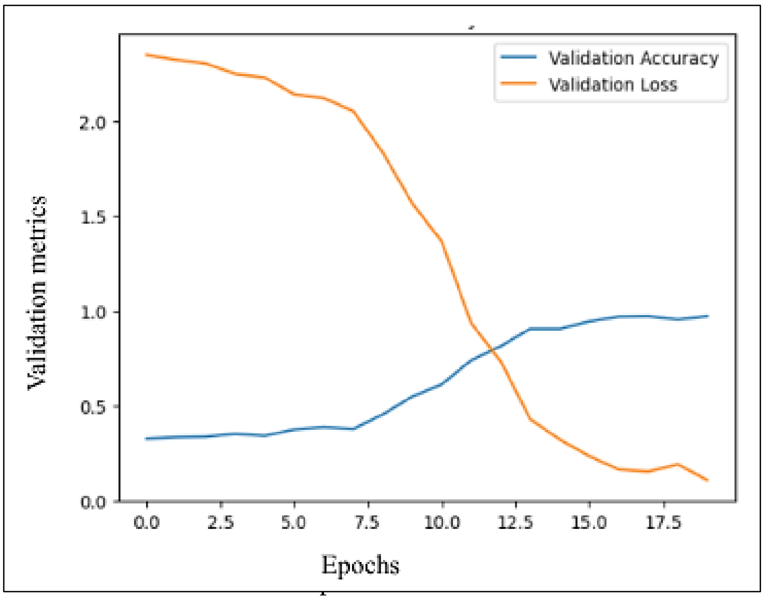

Figure 4: Validation Accuracy vs Loss

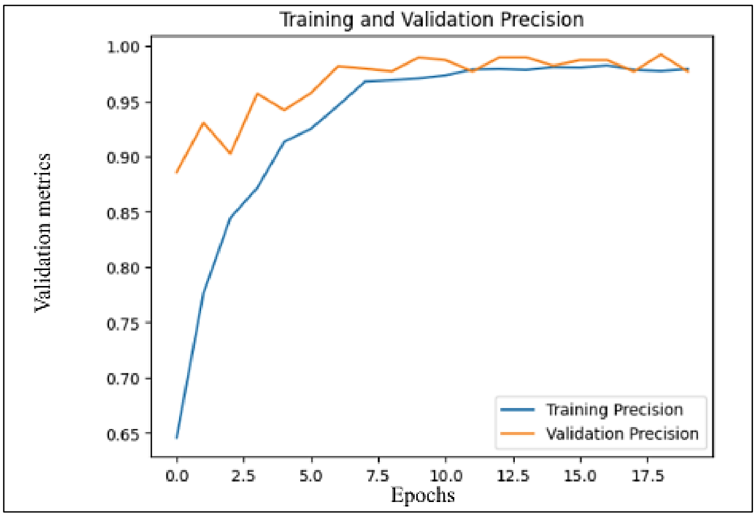

Figure 5: Training and Validation Precision

Data Preprocessing: The images were resized to 224x224 pixels and normalized to a range of (0, 1). Data augmentation was applied to increase the dataset's variability, which helps in preventing overfitting and improving the model's generalization.

Model Training: The training process involved tuning hyperparameters such as learning rate and batch size. Earlystopping was implemented based on validation accuracy to prevent overfitting.

Validation and Testing: Post-training, the model was validated on the validation set, and final testing was conducted on the test set. The results were logged and analyzed using the evaluation metrics mentioned above. The experiments were conducted within a robust MLOps framework, which ensured the reproducibility, version control, and scalability of the model:

Data Version Control (DVC): DVC was used to track changes in datasets and models, enabling reproducibility and collaboration across the team. The integration with Git ensured seamless version control without compromising the repository's size.

MLflow for Experiment Tracking: MLflow was employed to manage and track experiments. It logged all parameters, metrics, and artifacts, enabling easy comparison of different model versions and facilitating model management through its registry.

GitHub Actions for CI/CD: GitHub Actions automated the CI/CD pipeline, triggering tests, and validations on every commit or pull request. This ensured that only thoroughly tested and validated models were deployed.

Deployment on AWS: The final model was deployed on AWS using EC2 instances, with S3 for storage and Lambda for task automation. AWS provided the necessary scalability and reliability for real-time predictions. The integration of DVC, MLflow, GitHub Actions, and AWS into our experimental framework ensured a streamlined workflow from data collection to model deployment. This MLOps approach facilitated collaboration, reproducibility, and scalability, making the overall process efficient and reliable.

Error Analysis: Common errors include false positives in distinguishing benign from malignant conditions and false negatives in identifying rare disorders. These errors predominantly arise from underrepresented cases in the training set. Addressing this requires targeted data augmentation and improved preprocessing techniques.

Experimental Setup

- Dataset: Images resized to 224x224 pixels and normalized for consistency.
- Model Architecture: A MobileNetV2 backbone with a custom CNN for enhanced feature extraction.
- Data Augmentation: Random rotations, zooming, and flipping to improve generalization.
- Validation: Early stopping techniques ensured optimal model performance without over fitting.

Discussion

Skincare.ai UI/UX Overview

The user interface and experience (UI/UX) of Skincare.ai as shown in Figure 6 exemplify a well-thought-out design approach tailored to maximize accessibility and engagement. The homepage features a clean, responsive layout with a minimalistic aesthetic, prioritizing usability through a clear navigation bar and a prominently placed “Get Started” button. This entry point seamlessly directs users to the diagnostic tools. Key features include an intuitive drag-and-drop image upload functionality, supported by real-time feedback and a visually engaging progress bar during AI analysis. The results dashboard provides a structured presentation of detected conditions, complemented by confidence scores, interactive graphs, and actionable links to services such as teleconsultations, enhancing the platform's interactivity, the SkinBot Assistant as shown in Figure 7, available on all pages, supports both text and voice inputs, enabling users to access real-time assistance.

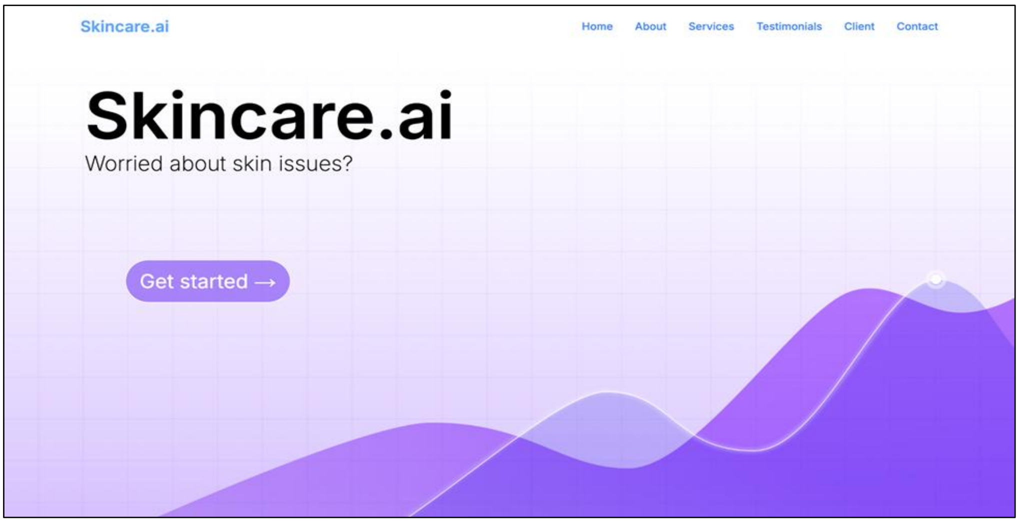

Figure 6: Website Photo

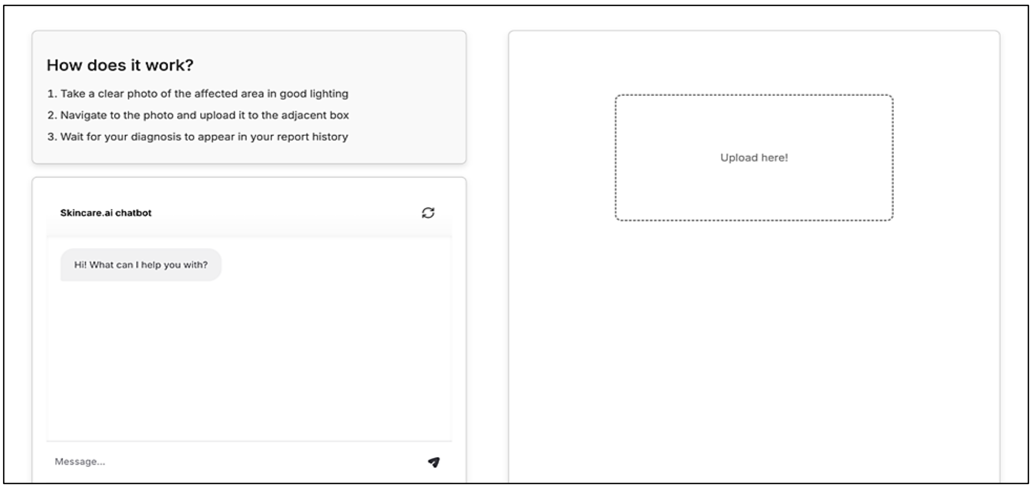

Figure 7: Website Photo

Figure 6 shows the user-friendly UI of Skincare.ai's homepage, emphasizing the clean layout and easy navigation tools to guide users. Figure 7 highlights the responsive design of the website, allowing users to easily upload images for diagnosis with real-time feedback. The platform's compliance with WCAG standards, its multilingual support, and personalization features—such as tracking results and notifications—highlight its inclusivity. Users have frequently commended Skincare.ai for its simplicity, responsiveness, and ability to provide a seamless experience, making it suitable for widespread adoption. The user interface and experience (UI/UX) of Skincare.ai exemplify a well-thought-out design approach tailored to maximize accessibility and engagement. The homepage features a clean, responsive layout with a minimalistic aesthetic, prioritizing usability through a clear navigation bar and a prominently placed “Get Started” button. This entry point seamlessly directs users to the diagnostic tools. Key features include an intuitive drag-and-drop image upload functionality, supported by real-time feedback and a visually engaging progress bar during AI analysis. The results dashboard provides a structured presentation of detected conditions, complemented by confidence scores, interactive graphs, and actionable links to services such as teleconsultations. Enhancing the platform’s interactivity, the SkinBot Assistant, available on all pages, supports both text and voice inputs, enabling users to access real-time assistance. The platform's compliance with WCAG standards, its multilingual support, and personalization features—such as tracking results and notifications—highlight its inclusivity. Users have frequently commended Skincare.ai for its simplicity, responsiveness, and ability to provide a seamless experience, making it suitable for widespread adoption.

Scalability Considerations for Skincare.ai

The scalability of Skincare.ai is essential for ensuring robust performance during high user demand, seamless healthcare integration, and efficient data management. Currently, the platform utilizes a cloud-based deployment designed for moderate traffic. Enhancements such as load balancing, container orchestration with Kubernetes, and serverless architectures can improve scalability to handle higher user loads effectively. Integration with healthcare systems remains limited. Incorporating protocols like HL7 or FHIR would facilitate smooth interaction with electronic medical records (EMRs) and telemedicine platforms. For data storage, while encrypted cloud storage is used, adopting scalable solutions like Amazon S3 or Google Cloud Storage, with regional redundancy and distributed databases, would provide optimized real-time data processing and enhanced reliability.These measures will prepare Skincare.ai for broader adoption, ensuring it remains efficient, secure, and capable of supporting extensive use in healthcare environments.

Anonymization Techniques and Security Measures

Skincare.ai prioritizes patient data protection through robust anonymization, encryption, and strict access controls. Patient images and personal details are anonymized before processing, ensuring no identifiable information is retained. Metadata, such as location and user details, is stripped from image files to maintain anonymity.

The platform employs AES-256 encryption for data storage and transmission, safeguarding against unauthorized access. SSL/TLS protocols secure all data exchanges, ensuring end-to-end encryption. Access to sensitive information is restricted to authorized personnel with proper clearance, while data retention policies ensure personal information is deleted after a set period unless legally required. This multi-layered approach aligns with healthcare data protection standards, ensuring confidentiality and user trust.

Ethical Considerations Surrounding AI

Ethical considerations surrounding AI in dermatology include algorithmic bias, which can occur if the AI models are trained on non-representative or biased datasets, leading to inaccurate diagnoses for underrepresented demographic groups, such as people with darker skin tones. This could perpetuate healthcare disparities. Additionally, potential harm arises from overreliance on AI without sufficient expert oversight, which may lead to misdiagnosis or inappropriate treatment recommendations. Ensuring transparency in how AI models make decisions, obtaining informed consent from patients, and regularly auditing algorithms for fairness and accuracy are crucial steps to address these concerns. Proper regulatory frameworks and continued research are necessary to minimize risks while promoting the safe use of AI in dermatology.

Future Directions for Skincare.ai

Future developments for Skincare.ai may include enhancing AI algorithms to detect a broader spectrum of skin conditions and providing personalized skincare recommendations tailored to individual needs. Expanding into real-time monitoring via wearable devices could offer continuous insights into skin health. Collaborations with healthcare providers to integrate teleconsultation and secure data exchange would strengthen clinical utility. Addressing scalability, privacy, and regulatory compliance will ensure ethical, secure, and widespread adoption. These advancements could position Skincare.ai as a global leader in AI-powered dermatology solutions.

Conclusion

Skincare.ai marks a breakthrough in AI-driven dermatological diagnostics, addressing key challenges such as bias, interpretability, and scalability. By utilizing explainable AI and robust evaluation metrics, the platform delivers reliable and transparent predictions, fostering trust among both clinicians and patients. Ethical considerations, including data privacy, algorithmic fairness, and inclusive representation, ensure Skincare.ai's suitability for diverse populations. As healthcare evolves, integrating ethical AI solutions like this is vital for closing gaps in access and accuracy. Future growth lies in expanding datasets to encompass rare and geographically diverse conditions, advancing predictive analytics, and exploring real-time edge computing. Collaborations with global healthcare stakeholders will keep Skincare.ai adaptable and innovative, aligning with emerging dermatological needs. In essence, Skincare.ai exemplifies how AI can democratize dermatological care, improve diagnostic accuracy, and reduce disparities, providing a strong foundation for equitable and effective healthcare solutions.

Abbreviation

Nil.

Acknowledgement

we would like to thank Vellore Institute of Technology for letting us use their labs for our research as well as providing us a space to conduct meetings and research.

Author contributions

All authors contributed to the study conception and design of the machine learning model and website.

Conflict of Interest

The authors declare that they have no competing interests.

Ethics Approval

Not applicable.

Funding

No funding received by any government or private concern.

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