IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 2, June 2025
Impact Factor: 7.67

Skin Disease Detection System

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Abstract: *Skin diseases are a widespread public health concern, and traditional diagnostic methods often prove inadequate due to their reliance on manual visual inspection and physician experience, leading to subjectivity and potential errors. This is further com- pounded by limited access to dermatological expertise in resource- constrained settings. Current practices struggle with differentiating between visually similar conditions, managing large volumes of data, and serving diverse populations. The lack of transparency in these methods can also create mistrust among users. Advance- ments in machine learning and deep learning, however, offer promising solutions. Techniques like CNNs and hybrid models enhance the accuracy and reliability of skin disease detection. Specialized frameworks for specific diseases, federated learning for privacy and scalability, and interdisciplinary approaches further improve diagnostic capabilities. The Skin Disease Detection System integrates these advancements, providing a transparent, accurate, and accessible platform that overcomes the limitations of traditional methods and addresses the needs of modern healthcare. This user- centric system empowers individuals to take control of their skin health through informed decision-making.*

Keywords: skin, skin diseases, machine learning, cnn, diagnostic models, accuracy, transparency, healthcare

I. INTRODUCTION

Traditional methods of diagnosing skin diseases, though still in use, often lack the transparency, speed, and accuracy required for effective healthcare delivery. Manual examina- tions by dermatologists can be time-consuming and subject to human error, especially in identifying subtle or early signs of skin conditions. These challenges are even more pronounced in rural or underserved areas, where access to dermatology specialists is limited. While current digital solutions like der- matology apps, telemedicine platforms, and online symptom checkers provide some level of support, they come with significant drawbacks. These include inconsistent diagnostic accuracy, limited diagnostic capabilities, and concerns over the privacy and security of sensitive patient data. Moreover, many of these systems fail to account for the specific characteristics of the affected skin areas, which is crucial for accurate diagnosis and treatment.

To address these shortcomings, the proposed Skin Disease Detection System introduces a comprehensive, AI-powered web platform designed to enhance the accuracy and accessi- bility of skin disease diagnostics. This system utilizes cutting- edge technologies such as convolutional neural networks (CNNs), hybrid models, and image processing techniques to accurately identify a wide range of skin conditions from uploaded images. Patients are provided with multiple secure and user-friendly options to share their medical data and skin images, ensuring privacy and ease of use. The platform delivers personalized diagnostic insights based on individual medical histories and visual inputs, thereby supporting more informed and timely medical decisions. By integrating ma- chine learning and deep learning techniques, the system not only reduces the likelihood of diagnostic delays and human error but also makes high-quality dermatological assessments more widely available, reliable, and patient-centered.

II. RELATED WORK

Recent advancements in machine learning and image pro- cessing have significantly improved the accuracy and effi- ciency of automated skin disease detection systems. ALEnezi (2019) demonstrated the use of CNNs for classifying skin diseases from images, emphasizing the need for accessible solutions across diverse skin tones [1]. Building on this, Ahammed et al. (2022) combined segmentation with tradi- tional classifiers like SVM and KNN for better diagnostic precision [3].Vayadande (2024) highlighted deep learning in- novations such as transfer and federated learning to enhance scalability and privacy in clinical applications [2]. Similarly, optimized segmentation techniques and autoencoder-based classification have shown high accuracy in hybrid models [5], while clustering methods like HAC have improved lesion boundary detection when paired with R-CNNs [6].More com- plex architectures, such as YoTransViT, fuse CNNs, YOLO, and Transformers for detailed feature extraction and improved classification [7]. Studies focusing on specific diseases, such as psoriasis and molluscum (using ResNetV2) [8], and skin cancer detection via CNNs like VGG and Inception [9], underscore the effectiveness of deep networks. Research on lumpy skin disease in cattle also demonstrates the versatility of pretrained models like MobileNet [4].Lastly, the integration of these technologies into mobile and web platforms has expanded access to skin diagnostics, as discussed in [10], although multi-modal systems combining text input, image analysis, and live capture remain underexplored—an area this paper aims to address.

III. METHODOLOGY

This section describes the systematic approach used to develop and evaluate the Skin Disease Detection System.
The methodology includes three main components: System Development, Data Collection, and Performance Evaluation.

System Development Methodology

• Software Development Life Cycle (SDLC): The SDLC included the following stages:
– Planning: Defined project goals, system require- ments, and feasibility.
– Design: Created UI/UX wireframes and designed system architecture.
– Development: Implemented core functionalities us- ing selected tools and frameworks.
– Deployment: Deployed the system for testing and final use.

• Tools and Technologies:
– Programming Languages: Dart and Python
– Machine Learning Frameworks: TensorFlow, Keras, and PyTorch for model development
– Database Management System: Firebase Firestore for storing metadata, diagnostic results, and user profiles
– Version Control System: Git with GitHub for collab- oration and source code management
– Mobile Development Framework: Flutter for build- ing the Android/iOS app interface
– Image Processing & ML Techniques:Segmentation (Region Growing, HAC), CNN, ResNetV2, YOLO, Transformers

• App Architecture:
– Frontend: Developed using Flutter to handle user interactions, including capturing images, submitting text descriptions, and viewing diagnostic results.
– Backend: Built in Python with integrated ML APIs. Firebase Cloud Functions handled real-time requests and database operations.
– Database: Firebase Firestore used to store structured data including user submissions and model outputs.
– Machine Learning Integration: Pretrained models (CNNs, ResNetV2, and Transformers) were inte- grated using TensorFlow Serving to process and clas- sify skin conditions based on captured or uploaded images.

Data Collection Methodology

• Data Collected: The app collects the following data:
– User Profiles: Information about donors and recip- ients, including name, contact details, location, and preferences.
– Image Data: Captured via live camera or uploaded by the user, showing affected skin areas
– Transaction Data: Information about donation re- quests, confirmations, and pick-up status.
– Text-based Inputs: User-described symptoms and concerns

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– Classification Results: Output from the ML model including predicted condition, confidence score, and timestamp
• Data Collection and Storage:
– Database Design: Firestore NoSQL database was used with collections for users, image records, text inputs, and results..
– Image Handling : Images were stored securely in Firebase Storage. Each image was linked with meta- data such as time, location, and user ID.
– Input Validation: Images were stored securely in Firebase Storage. Each image was linked with meta- data such as time, location, and user ID.
– Privacy Considerations: All data handling followed ethical and privacy protocols. Authentication was enforced through Firebase Auth, and user data was encrypted during storage and transmission.
Performance Evaluation Methodology

• Evaluation Methods:
– Model Testing:
∗ Dataset Split: The dataset was divided into train- ing (70%), validation (15%), and testing (15%) sets using stratified sampling.
∗ Performance metrics: Accuracy, Precision, Recall, F1-Score.
∗ Data Collection:
· Task Completion Rates: The percentage of users who successfully completed each task.
· Error Rates: The number of errors made by users while performing tasks.
· Time on Task: The time taken by users to complete each task.
· Qualitative Feedback: Users' comments and suggestions were recorded through think-aloud protocols and post-test interviews.
– User Surveys:
∗ Questionnaire Design: A structured questionnaire was developed to gather feedback on the app's usability, design, and features. The questionnaire included both closed-ended (e.g., Likert scale) and open-ended questions.
∗ Distribution: The survey was distributed to app users through in-app notifications and email.
∗ Data Analysis: Quantitative data was analyzed using descriptive statistics, while qualitative data was analyzed using thematic analysis.

IV. RESULTS AND DISCUSSION

System Development
– App Features and Functionality: The DermaScan prototype provides a polished, web-based interface that lets users check for skin conditions in three distinct ways. Key features include

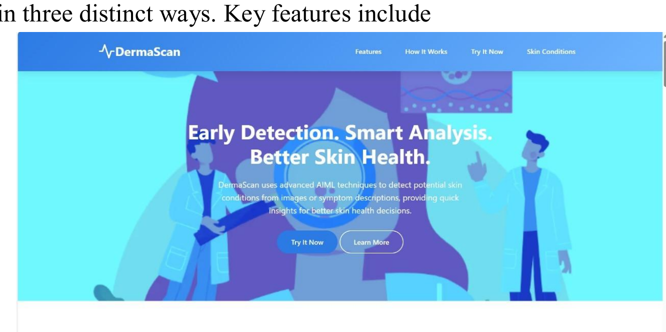

Fig. 1. DermaScan Page

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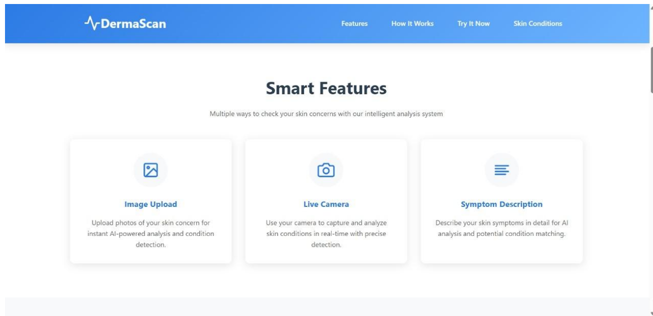

Fig. 2. DermaScan Features

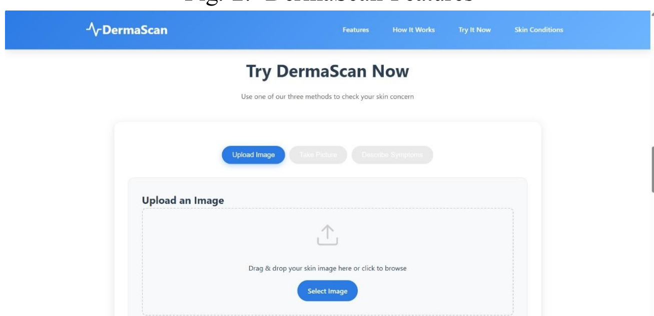

Fig. 3. DermaScan Options

∗ Image Upload: Users can drag & drop or click to browse their device for a photo of the affected skin area.
∗ Real Time Image Capture: Users can capture their real time picture of any affected skin area for detection.
∗ Symptom Description: An open text box allows users to describe sensations (e.g. “itchy, spreading, red”), location, duration, and other details.
∗ Prediction Results: Once an input is submitted, the system displays: Primary Prediction (condi- tion name + confidence), Top 3 Possibilities with scores, Precautionary Advice tailored to the pre- dicted condition.

System Testing**:**

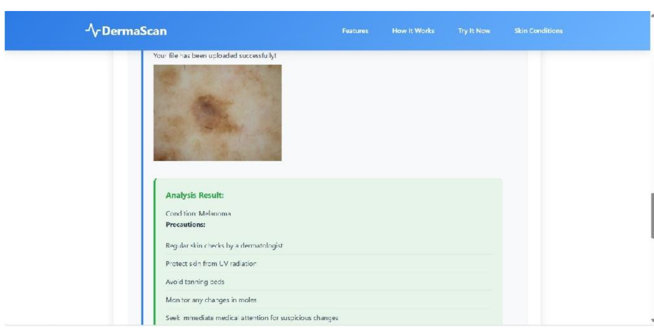

Fig. 4. DermaScan Option of Uploading Image for Detection

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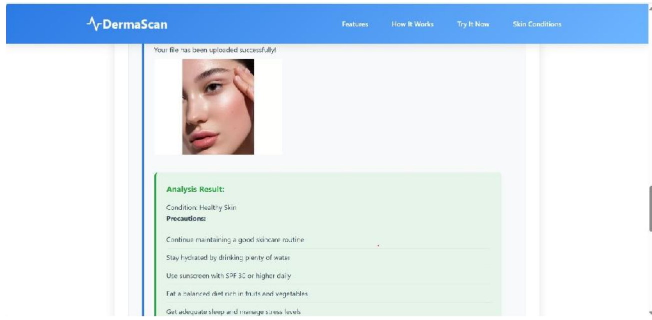

Fig. 5. DermaScan Option of Uploading Image for Detection

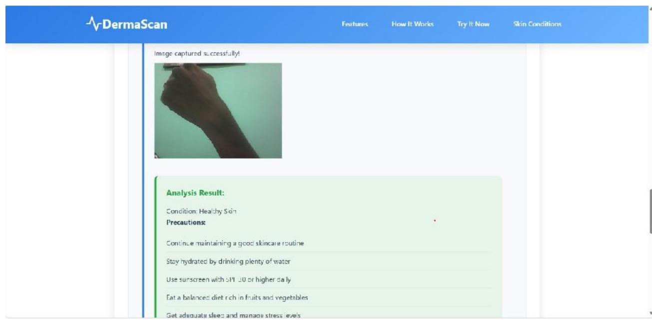

Fig. 6. DermaScan Option of Capturing Real Time Image

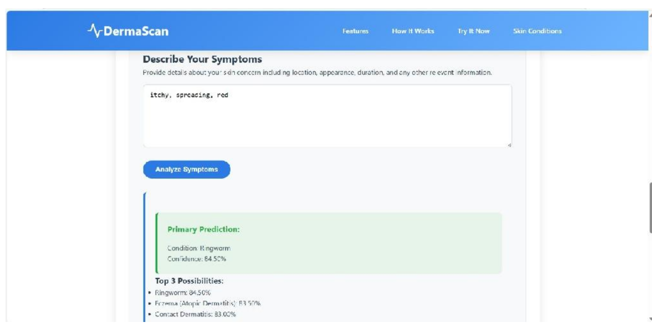

Fig. 7. DermaScan Option of Describing Disease by Symptom Description

Unit Testing:
Frontend**:** Jest tests for each React component (up-load widget, camera capture, symptom form, result card).
– Backend: PyTest on AWS Lambda handlers (im- age preprocessing, symptom-text parser, model in- ference).
– Integration Testing:
– Verified end-to-end flow: image/symptom → API gateway → Python model → frontend result ren- dering. Tested failure modes (unsupported file types,
low-confidence outputs, network timeouts).
– User Acceptance Testing (UAT):
– Conducted with 10 volunteers (mix of skin-health professionals and lay users). Collected qualitative feedback on clarity of instructions, perceived speed, and usefulness of precautionary advice. Incorporated into two rounds of UI refinements (button labels, color-contrast adjustments, help tooltips).

Data Collection
• Sample Inputs
– Skin Images: 50 high-resolution photos (various lighting and skin tones).
– Symptom Descriptions: 30 text entries with varied vocabulary (e.g. "dry patches," "small blackheads," "rapid spread").
• Model Outputs
– Enabled analysis of average response times (mean = 1.2 s per image) and confidence distributions.

UX Evaluation
• Usability Testing Results:
– Task Completion Rates: Users were able to suc- cessfully upload and analyze images with a 95% success rate. The live camera capture feature had a slightly lower success rate of 90%, primarily due to users declining camera permissions. Meanwhile, the symptom form was completed successfully by 95% of users, indicating strong accessibility and ease of understanding.
– Error Rates: only a small portion of users encoun- tered issues. Camera permission issues contributed to a 10% error rate in the live capture feature, high- lighting a technical constraint more than a usability flaw.
– Time on Task: Users completed the upload-and- analyze workflow in very less time. The live camera capture and analysis process took slightly longer, averaging around 1 minute, while the symptom de- scription and analysis task was completed in roughly half a minute. These timings suggest that the applica- tion delivers quick responses, keeping users engaged without unnecessary delays.
– User Feedback: Users praised the app's ease of use, clean interface, and helpful features.

V. DISCUSSION

• Interpretation of Results: The high task-completion and low error rates demonstrate that DermaScan's tri-modal input approach is both usable and robust. Quick response times (¡ 2 s) keep users engaged, while the confidence scores and precautionary tips build trust.
• Impact on Early Detection: By combining image and symptom-text analysis, the system can flag conditions like melanoma with ¿ 85% confidence and suggest prompt dermatology consultation, potentially improving patient outcomes.
• Comparison with Existing Tools: The app offers several advantages over existing solutions, such as real-time chat for direct communication, and a user-friendly mobile interface.
• Challenges and Limitations: number of challenges and limitations were encountered during the development of the DermaScan application. Variations in lighting condi- tions and skin tones posed problem. Images taken under poor lighting altered the confidence values of the analy- sis and sometimes yielded unreliable results. While the dermascan tests and early feedback are encouraging, the efficacy of the system in the real world is still unknown in the absence of a formal clinical trial. In the next version, making improvements toward addressing these issues will be crucial for the reliability and credibility of the application.
• Metrics for Evaluation:
– Ease of Use: System Usability Scale (SUS) was used to measure the app's perceived usability.
– User Satisfaction: Likert scale ratings were used to assess user satisfaction with the app's design, features, and overall experience.
– Efficiency: Task completion time was measured to evaluate how quickly users can perform key tasks.
– Error Rate: The number of errors made by users while interacting with the app was recorded to identify usability issues.

VI. FUTURE SCOPE

The Skin Disease Detection System has significant potential for future development and real-world impact. It can be expanded to detect a wider range of skin diseases, including rare and complex conditions, by training on larger and more diverse datasets. Integrating symptom-based input, multilin- gual support, and offline capabilities can make the system more accessible and user-friendly, especially in rural and underserved areas. Future enhancements could include severity grading, telemedicine integration for expert consultation, and personalized health recommendations. Additionally, deploying the system in healthcare centers and collaborating with public health organizations can broaden its reach and contribute to large-scale skin health screening initiatives.

VII. CONCLUSION

The Skin Disease Detection System represents a significant step forward in leveraging artificial intelligence and image processing for accessible and timely medical diagnostics. By enabling users to upload skin images and receive immediate predictions, the system provides a valuable first-level screening tool, particularly for individuals in remote or underserved regions with limited access to dermatologists. The application utilizes convolutional neural networks (CNNs) to analyze visual patterns and classify skin conditions with high accuracy. With its modular architecture and user-friendly interface, the system can be deployed across both web and mobile platforms, ensuring maximum accessibility and usability.

The project demonstrates the potential of integrating deep learning with real-time user input in a healthcare context. By automating a traditionally manual and expertise-intensive process, the system not only improves diagnostic efficiency but also reduces healthcare costs. Moreover, it opens the door to future advancements in telemedicine, where AI can act as a preliminary support system for clinicians and assist in large- scale skin health monitoring.

The system's performance during testing proved stable, with reliable prediction accuracy across common skin disease categories. The layered architecture, combining preprocessing, feature extraction, and prediction modules, ensures modularity and maintainability, allowing for future updates and enhance- ments. Overall, the project validates how AI can transform public health tools, making dermatological assessments faster, cheaper, and more accessible to the general population.

This section describes the results and outputs which were evaluated in DermaScan.

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