Skin-Sense: An AI Based Skin Disease Detection System

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Abstract:
Skin diseases have become increasingly common due to environmental changes, lifestyle factors, and limited availability of dermatological services. Early identification of skin disorders is essential to prevent complications and to support timely treatment. This paper presents the implementation of an artificial intelligence-based skin disease detection and management system that analyzes skin images to assist users in identifying possible skin conditions. The system enables users to upload or capture images of affected skin areas and optionally provide visible symptom information to improve prediction reliability. A deep learning–based image classification model is employed to process the input images and generate predicted disease results along with confidence scores. In addition to disease detection, the platform provides preventive guidance, basic care recommendations, automated report generation, and healthcare support features such as chatbot assistance and doctor appointment facilitation. The implemented system aims to improve accessibility to preliminary dermatological assessment, reduce dependence on immediate physical consultations, and promote early awareness and management of skin-related health issues.

Keywords: Skin Disease Detection, Deep Learning, CNN, Computer Vision, Healthcare System, Image Processing, AI in Healthcare.

I . INTRODUCTION

Skin diseases represent one of the most common categories of health disorders worldwide, affecting people of all age groups and skin types. These conditions range from mild infections and allergic reactions to chronic disorders and serious illnesses such as skin cancer. In many cases, the visual similarity between different skin diseases makes early and accurate diagnosis difficult without expert consultation. Moreover, limited access to dermatologists, high consultation costs, and long waiting times often result in delayed diagnosis and improper self-treatment, especially in rural and underserved regions. Recent advancements in artificial intelligence, particularly in deep learning and computer vision, have demonstrated strong potential in medical image analysis. Convolutional Neural Networks (CNNs) and related architectures have achieved remarkable performance in tasks such as image classification, object detection, and pattern recognition, making them well-suited for automated skin disease analysis. By learning discriminative visual features from large datasets of skin lesion images, these models can assist in identifying possible skin conditions with considerable accuracy.

This work focuses on the implementation of an AI-based skin disease detection and management system that provides users with a preliminary assessment of skin conditions through image analysis. The system allows users to upload or capture images of affected skin areas and optionally input visible symptoms to enhance diagnostic reliability. The backend integrates a deep learning–based classification model to process images and generate predicted disease labels along with confidence scores. Beyond detection, the system incorporates healthcare support features such as preventive guidance, chatbot-based assistance, automated report generation, and doctor appointment facilitation. The primary goal of this implementation is to develop a practical, user-friendly platform that supports early identification of skin disorders, improves public awareness, and encourages timely medical consultation. By combining artificial intelligence with digital healthcare tools, the system aims to reduce dependency on immediate physical visits and to make preliminary dermatological support more accessible

II. LITERATURE SURVEY

Narendra (2024) introduced a multimodal skin disease detection framework that combines skin lesion images with textual symptom descriptions provided by users. The system processes images using convolutional neural networks while natural language processing techniques are applied to symptom text. Both modalities are fused to produce a final prediction. The integration of a chatbot-based interface enabled remote accessibility and improved user interaction. Although the approach demonstrated promising classification performance, its effectiveness strongly depended on the quality of both user-provided images and textual inputs, highlighting challenges in real-world deployment.

Balasundaram et al. proposed an ensemble-based deep learning model optimized using a genetic algorithm. Multiple pre-trained CNN models were combined through a stacking strategy, where the genetic algorithm automatically selected optimal model combinations and hyperparameters. The system achieved improved accuracy on large benchmark datasets such as DermNet and HAM10000. This work demonstrated that automated ensemble optimization can outperform manually designed models; however, it also introduced higher computational cost and training complexity.

Riaz et al. presented a joint learning framework for skin cancer detection that fused deep CNN features with handcrafted texture descriptors such as Local Binary Patterns. By combining structural and textural information, the system achieved higher classification accuracy than single-feature approaches. The results highlighted the importance of feature fusion in improving robustness, though the reliance on controlled datasets raised concerns about real-world generalization.

Liu (2025) proposed a deep learning architecture that integrates multi-scale feature fusion with spatial and channel attention mechanisms. This design enhanced the model's ability to focus on clinically relevant lesion regions while suppressing background noise. The attention-based framework significantly improved classification performance, particularly in cases involving visually similar skin conditions. However, the study primarily evaluated curated datasets, indicating a need for further validation on smartphone-captured images.

III. CONCLUSION OF LITERATURE SURVEY

Overall, existing research confirms that deep learning models, especially CNN-based and attention-enhanced architectures, are highly effective for skin disease classification. However, many prior works mainly focus on improving model accuracy and lack practical system-level features such as symptom input, reporting, and healthcare assistance tools. The present implementation builds upon these foundations by integrating deep learning–based image analysis with user-oriented healthcare support features to enhance real-world applicability

IV. DATASET DESCRIPTION

The dataset used in this study is the Skin Disease Detection Dataset, which is publicly available on Kaggle and specifically designed for multi-class skin disease classification tasks. This dataset consists of high-resolution dermatological images categorized into various disease classes, making it highly suitable for training robust deep learning models.

A. Dataset Organization

To facilitate effective supervised learning, the dataset is organized into two primary directories:

- Training Set (train/): Contains labeled images grouped into folders corresponding to the different disease classes used for model optimization.
- Validation Set (val/): Utilized for evaluating model performance and ensuring generalization during the training process.

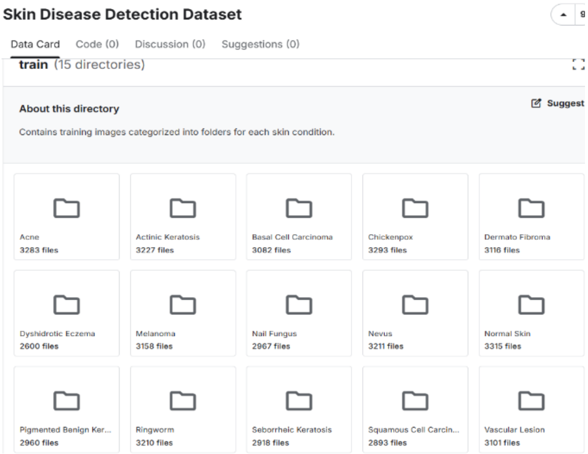

Fig. 1: Dataset Preview

B. Disease Categories

The dataset encompasses the following 15 distinct skin disease categories, providing a comprehensive range of conditions for the AI model to analyze:

1. Acne
2. Actinic Keratosis
3. Basal Cell Carcinoma
4. Chickenpox
5. Dermatofibroma
6. Dyshidrotic Eczema
7. Melanoma
8. Nail Fungus
9. Nevus
10. Normal Skin
11. Pigmented Benign Keratosis
12. Ringworm
13. Seborrheic Keratosis
14. Squamous Cell Carcinoma
15. Vascular Lesion

C. Data Preprocessing

Each image in the dataset is individually labeled according to its corresponding disease class. During the implementation phase, these images undergo several preprocessing steps, including resizing, normalization, and noise reduction to ensure uniformity. Additionally, data augmentation techniques such as rotation and flipping are applied during training to improve model robustness and reduce the risk of overfitting.

V. METHODOLOGY

The implemented system follows a structured approach that integrates deep learning–based image analysis with a web-based application framework. The overall methodology consists of image acquisition, preprocessing, model-based classification, and result delivery. Initially, users upload or capture images of affected skin areas through the application interface. The received images are pre-processed to ensure uniformity, including resizing, normalization, and noise reduction. Data augmentation techniques such as rotation and flipping are applied during training to improve robustness and reduce overfitting.

A convolutional neural network–based deep learning model is employed to extract discriminative visual features and classify skin diseases. The model is trained on labelled skin image datasets using supervised learning. During training, prediction errors are minimized using backpropagation and gradient-based optimization. After validation, the trained model is deployed on the backend server for real-time inference.

The backend processes user requests, performs image preprocessing, and forwards the images to the trained model. The predicted disease label and confidence score are then generated and stored in the database. The system presents the results to the user along with basic preventive guidance and report generation support. Additional healthcare assistance modules, such as chatbot interaction and doctor appointment facilitation, are integrated to enhance real-world usability.

VI. SYSTEM ARCHITECTURE

The architecture of the "Skin-Sense" system is designed to provide a seamless interface between the user and the deep learning backend. It follows a structured workflow to handle data from initial acquisition to final healthcare support.

A. Block Diagram

The block diagram illustrates the sequential flow of information within the application. The process begins with the user interacting with the web or mobile interface to provide data. This data is processed by the backend server, which manages the core logic of the system.

- Image Preprocessing: Raw images are cleaned and normalized to ensure high-quality input for the AI model.
- AI Model (CNN): The core convolutional neural network analyses the processed image to identify potential skin conditions.
- Prediction & Report Unit: This module generates the final diagnosis and formats it into a user-friendly report.
- Support Modules: Integrated features like chatbot assistance and doctor appointment facilitation provide immediate next steps for the user.

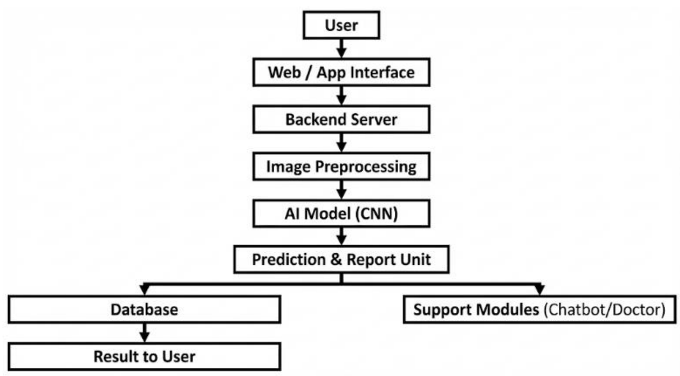

Fig. 2: Block Diagram

B. System Architecture Workflow

The system architecture represents the high-level integration of the dataset, the trained model, and the functional application.

- User Interaction: Users can upload images or select specific symptoms through the system interface.
- Database Management: The system securely sends data to and receives acknowledgments from the database to maintain patient records.
- Model Lifecycle: The architecture incorporates the entire pipeline from Dataset Creation and Cleaning to Model Training and the final Model Save, which is then used for real-time processing.
- Output Delivery: Final results are categorized by disease type and paired with Prevention & Product Recommendations to offer comprehensive care.

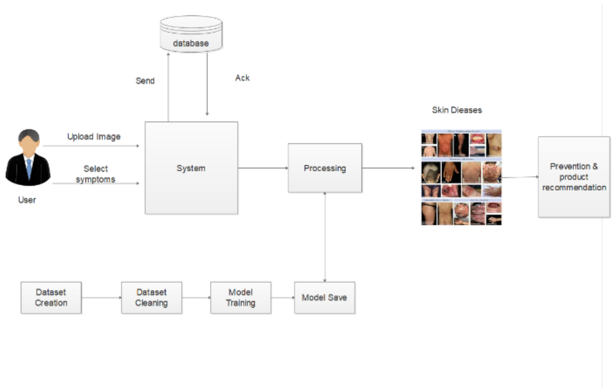

Fig. 3: System Architecture

VII. OBJECTIVE

1. To design and implement an AI-based system that can analyze skin images and predict possible skin diseases using deep learning techniques.
2. To develop an automated platform that allows users to upload skin images and obtain disease predictions along with confidence scores.
3. To integrate supportive healthcare features such as preventive guidance, chatbot assistance, and medical report generation to enhance usability.
4. To provide a user-friendly digital solution that promotes early detection and encourages timely medical consultation.

VIII. PROBLEM DEFINATIONS

Skin diseases are among the most common health issues worldwide, yet early and accurate diagnosis remains challenging due to limited access to dermatologists, high consultation costs, and the visual similarity between many skin conditions. In many cases, people delay medical attention or rely on unreliable self-assessment, which can lead to improper treatment and worsening of disease.

The problem addressed in this work is the lack of an accessible, low-cost, and reliable preliminary system for identifying skin diseases. There is a need for an AI-based solution that can analyse skin images, provide early indications of possible conditions, and assist users with basic guidance and healthcare support, thereby encouraging timely professional consultation

IX. SYSTEM REQUIREMENTS

To ensure the "Skin-Sense" platform operates effectively as both a diagnostic tool and a healthcare management system, the following requirements have been established.

A. Functional Requirements

The functional requirements define the specific behaviors and services the system must provide to the end-user.

- User Authentication: The system shall allow users to register and securely log in to the platform.
- Image Acquisition: The system shall allow users to upload or capture images of affected skin areas.
- Preprocessing and Analysis: The system shall preprocess the uploaded images and forward them to the AI model for analysis.
- Disease Prediction: The system shall predict the possible skin disease and display the result with a confidence score.
- Preventive Guidance: The system shall provide basic preventive guidance and care suggestions based on the prediction.
- **Report Generation:** The system shall generate and allow users to download a diagnostic report in PDF format.
- **Healthcare Assistance:** The system shall support additional assistance features such as chatbot interaction and doctor appointment facilitation.

B. Non-Functional Requirements

The non-functional requirements specify the quality attributes and constraints under which the system must operate.

- Performance: The system should process images and display prediction results within a few seconds.
- Accuracy: The AI model should provide reliable predictions when given clear and properly captured images.
- Usability: The interface should be simple, intuitive, and accessible to users with minimal technical knowledge.
- Scalability: The system should support multiple users simultaneously without significant performance degradation.
- Security: User data and uploaded images must be securely stored and protected against unauthorized access.
- Reliability: The system should maintain high availability with minimal downtime.
- Compatibility: The system should function smoothly across major web browsers and devices.

X. RESULTS

The experimental results of the "Skin-Sense" system highlight the successful training of the CNN-based deep learning model and its seamless integration into the healthcare management platform. The following figures and descriptions detail the model's performance and the system's output.

A. Model Development and Training Logs

The system utilized a Convolutional Neural Network architecture, specifically optimized for multi-class dermatological classification.

- Model Creation & Save: The architecture was initialized and saved as a deployment-ready artifact (e.g., .keras or .h5 format) to ensure real-time inference on the backend server.
- Training Logs: The training process involved mapping visual features to 15 distinct disease categories using the Adam optimizer with a learning rate of 0.0001.

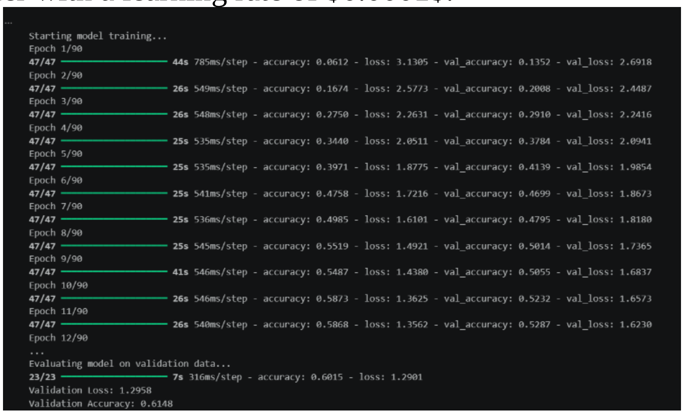

Fig. 4: Training

B. Evaluation Metrics

The model was evaluated using a structured validation dataset to measure its generalization capabilities.

- Epochs Performance: The model was trained for 90 epochs, demonstrating a steady convergence in both training and validation phases.
- Validation Accuracy: The system achieved a final Validation Accuracy of 61.48%, indicating a reliable ability to classify complex skin conditions.
- Validation Loss: The final Validation Loss was recorded at 1.2958, confirming consistent error reduction.

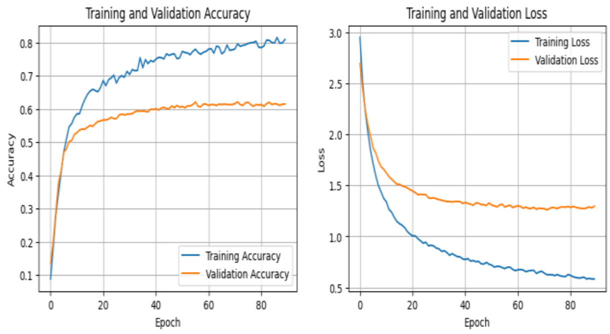

Fig.5: Testing & Validation

C. System Delivery and Functional Results

The results confirm that the "Skin-Sense" platform meets its core functional objectives by providing a user-friendly diagnostic experience.

- Real-Time Inference: The web interface allows for seamless image acquisition, returning predicted labels and confidence scores (e.g., 96.96% for Acne) in seconds.
- Automated Reporting: Upon prediction, the system generates a comprehensive PDF diagnostic report containing symptoms, precautions, and product recommendations.
- Supportive Modules: Integration testing confirmed the functionality of the doctor appointment facilitation and chatbot interaction modules.

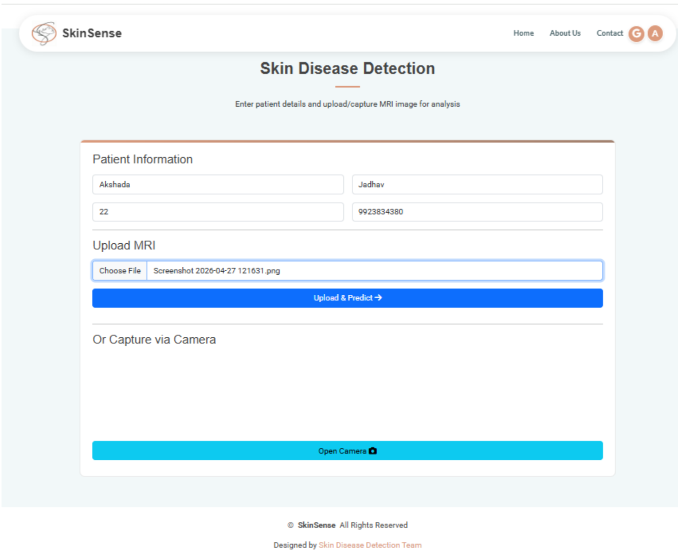

Fig. 6: Web interface for data entry

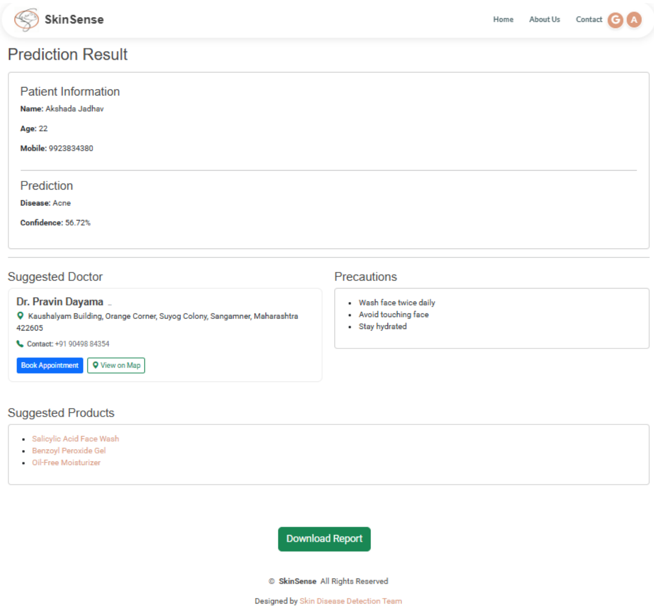

Fig. 7: Prediction output

Fig. 8: summary report in PDF format.

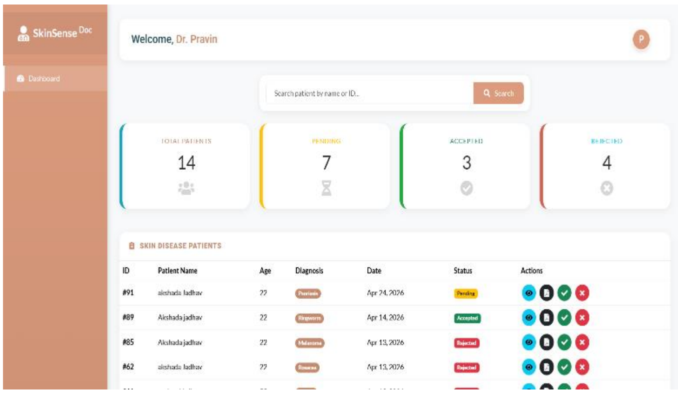

Fig. 9: Doctor's Dashboard

XI. CONCLUSION

This paper presented an AI-based skin disease detection and management system designed to assist users in the early identification of skin conditions. By leveraging deep learning techniques, particularly convolutional neural networks, the system analyzes skin images and predicts possible diseases with associated confidence scores.In addition to disease prediction, the system integrates supportive healthcare features such as preventive guidance, chatbot assistance, report generation, and doctor appointment facilitation. These features enhance the practical usability of the system and make it more accessible to users, especially in areas with limited dermatological services.The proposed system aims to reduce delays in diagnosis, promote early awareness, and encourage timely medical consultation. Future work may focus on improving model accuracy using larger real-world datasets and deploying the system on mobile platforms for wider accessibility..

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