INTELLIGENT DERMATOLOGY ASSISTANT – AI BASED DIAGNOSIS AND MEDICINE RECOMMENDENDATION

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Abstract

Skin diseases are among the most common health concerns worldwide, and early diagnosis is crucial to prevent complications and reduce treatment costs. Manual diagnosis requires expert dermatological knowledge and is time-consuming, especially in remote areas with limited access to specialists. This paper proposes an Intelligent Dermatology Assistant, an AI-driven system capable of identifying multiple skin diseases from images, predicting severity, and recommending appropriate medicines and dermatologist information. The system integrates deep learning-based image classification using a CNN model, imputation strategies for handling missing or inconsistent metadata, and a Streamlit-based interactive interface for real-time diagnosis. The model is trained on a curated dataset of skin disease images and achieves improved accuracy through preprocessing, augmentation, and finetuning. The system also provides disease descriptions, causes, deficiencies, and personalized treatment guidelines. Experimental results demonstrate the model's reliability and suitability for practical deployment as a clinical decision support tool.

Keywords— Dermatology, Deep Learning, Skin Disease Classification, CNN, Medicine Recommendation, Data Imputation, Streamlit, AI in Healthcare.

I. INTRODUCTION

Skin diseases affect millions of individuals globally, and many conditions—such as eczema, psoriasis, acne, dermatitis, and fungal infections—require early recognition to avoid complications. Traditional diagnosis relies heavily on dermatologists' expertise, which makes early detection difficult in rural or underserved regions. With the Streamlit to enable real-time image uploads and instant diagnosis. This makes the solution suitable for both clinical and personal use.Even with the improvements in imputation techniques, there

II. RELATED WORK

Deep learning has been widely adopted in medical image analysis, particularly in dermatology. Early computer-aided diagnostic systems leveraged handcrafted feature extraction techniques, but recent advancements in CNNs significantly improved performance in detecting complex dermatological patterns. Popular architectures like ResNet, MobileNet, VGG, and DenseNet have been extensively used for skin lesion classification.

automated dermatology systems have become promising tools for early screening and tele-health consultations.

To overcome these limitations, advanced imputation techniques have been proposed, such as K-Nearest Neighbors (KNN) and deep learning-based techniques, like autoencoders. The KNN imputation technique works on the principle that similar data points should have similar values. By averaging the values of the K nearest neighbors to a missing value, KNN can make more accurate imputations, especially in data where features have local correlations. KNN, however, is computationally inefficient for high-dimensional data since the distance metric between examples becomes less effective with preprocessing, cleaning, imputation, augmentation, CNN training, and system deployment. Each component is designed to improve prediction accuracy and ensure a seamless user experience.

A.Dataset Upload and Input Layer

1. Users upload skin images through the Streamlit interface.
2. Training datasets contain labeled images of multiple skin diseases.
3. Metadata such as disease name, severity, and category is validated for completeness.
4. Missing labels or undefined metadata fields are handled using imputation techniques such as KNN or frequencybased filling to maintain dataset consistency.

- KNN Imputation: Replaces missing values based on similarity with neighboring samples.
- Rule-Based Imputation: Maps missing disease names using symptom-keyword matching.

This ensures that the model receives a complete and consistent dataset.

C. Preprocessing and Cleaning

1. Images are resized to 224×224×3 to match CNN input requirements.
2. Pixel values are normalized for training stability.
3. Noise reduction filters remove blur, artifacts, and pixel noise.

Several studies highlight the importance of preprocessing and data augmentation to generalize deep models for variable lighting conditions, skin tones, and camera resolutions. Research also shows that integrating metadata—such as age, region, and symptoms—can improve diagnostic accuracy. However, missing metadata is a common issue in clinical datasets. To mitigate this, **imputation methods** such as mean imputation, mode substitution, KNN-based imputation, and deep-learning-based autoencoder imputation are widely used.

Previous systems mainly focus on classification accuracy but do not provide a comprehensive diagnostic platform with treatment recommendations, severity analysis, or specialist mapping. Existing web-based dermatology applications are limited to single-disease detection or symptom-based suggestions. The proposed system addresses these gaps by combining **AI-driven diagnosis** with **medicine recommendations, deficiency analysis, and dermatologist details** to deliver a holistic digital dermatology assistant.

The methodology consists of several stages: dataset preparation,

III. METHODOLOGY

4. Poor-quality or corrupted images are automatically discarded.

D. Data Augmentation

To avoid overfitting and expand dataset diversity, the following transformations are applied:

- Rotation
- Horizontal/vertical flip
- Brightness and contrast variation
- Zoom and crop
- Minor distortions

This strengthens the model's ability to handle real-world variations.

E. CNN Model and Feature Extraction

The system uses a pre-trained network (ResNet/MobileNet) for transfer learning.

Steps include:

1. Base CNN weights frozen to retain learned features.
2. Custom dense layers added for classification of specific skin diseases.
3. Softmax layer outputs disease probabilities.
4. Training optimized using Adam optimizer with early stopping.

F. Severity Assessment

Confidence scores are mapped to severity levels:

- >80% – Mild
- 60–80% – Moderate
- <60% – Severe

This provides clinically relevant insights beyond classification.

G. Medicine and Doctor Recommendation Engine A knowledge-based system maps each predicted disease to:

- recommended medicines,
- causes,
- deficiencies,
- treatment guidelines,
- dermatologist contact details.

Recommendations are validated using medical reference data.

H. Streamlit Deployment

The entire system is built into an interactive application featuring:

- real-time image upload,
- disease prediction dashboard,
- medicine suggestions panel,
- severity indicator, • dermatologist list, • downloadable PDF report.

Streamlit ensures fast deployment with an intuitive interface.

IV. SYSTEM ARCHITECTURE

The Intelligent Dermatology Assistant is designed as a multilayered architecture that integrates image preprocessing, deep learning–based disease prediction, knowledge-driven medicine mapping, and user-interactive reporting. The system is implemented using Python, TensorFlow/Keras, NumPy, Streamlit, and FPDF, ensuring both computational efficiency and user accessibility. The complete architecture reflects the actual workflow present in the codebase.

1. User Interaction Layer (Streamlit Front-End)

This layer provides an intuitive interface for patients to upload skin images, enter age, and navigate different service modules. It includes:

- Navigation Tabs: Upload & Predict, Disease Info, Medicine Recommendation, Doctor Recommendation, Report Download.
- File Upload System: Accepts JPG/PNG and converts them into RGB.
- Session Management: Saves the prediction, user age, and processed image using st.session_state.
- Custom UI Styling: CSS-based enhancement for cards, confidence bars, and severity colors.

Role: Collects user inputs and sends them to the prediction engine.

2. Input Acquisition and Validation Layer Once the user uploads an image, the system performs:

- Format Validation (JPG/JPEG/PNG).
- Image Conversion via PIL (Image.open().convert("RGB")).
- Age Validation using numeric constraints.

This ensures only clean and correctly formatted data moves forward to the model.

3. Preprocessing Layer

Before inference, the uploaded image is standardized to match the CNN model's input requirements:

- Resize to 224×224 pixels
- Normalization to 0–1 range
- Conversion to NumPy array
- Addition of batch dimension (np.expand_dims)

This stage ensures consistency with the pre-trained TensorFlow model (dermatology1_assistant_model.keras).

4. Deep Learning-Based Classification Layer

This is the computational core of your system.

- Model Used: Loaded via load_model() (TensorFlow Keras).
- Output: 23-class softmax probabilities.
- Mapping: Output index → disease name (using model_classes dictionary).
- Confidence Score: np.max(pred)*100
- Severity Category:
  - Mild → >80%
  - Moderate → 60–80%
  - Severe → <60%

The prediction function encapsulates this logic (predict_from_model()), returning a structured dictionary with all details.

5. Disease Knowledge Base Layer

Your code contains a structured dictionary (disease_info) which acts as a compact knowledge base.

Each disease record contains:

- Description
- Recommended Medicines (with icons + WebMD links)
- Assigned Dermatologist
- Optional Deficiency or Cause Info

This static data allows the system to enrich pure CNN output with contextual medical advice.

6. Recommendation Layer

This layer generates personalized recommendations:

a. Medicine Recommendation

Powered by prediction["medicines"] list. Displays:

- Medicine name
- Icon
- Clickable medical reference link

b. Doctor Recommendation

Your code pulls doctor names from the knowledge dictionary and enables:

- Appointment booking form
- Google Maps search link generation using:
- urllib.parse.quote(prediction['doctor'])

c. Severity & Explanation Severity color coding:

- Green (Mild)
- Orange (Moderate)
- Red (Severe)

This improves clinical interpretability.

7. Reporting and Export Layer (FPDF Engine)

The system generates a downloadable medical report using FPDF, containing:

- Patient age
- Predicted disease
- Confidence score
- Severity level
- Recommended doctor
- Medicines with links The PDF is exported using: pdf.output("report.pdf") and made downloadable with Streamlit's st.download_button.

8. Session Memory & Navigation Layer

Streamlit's internal state (st.session_state) is used to store:

- Uploaded image
- Prediction results
- Age input

This enables seamless navigation across pages without re-running predictions.

9. Deployment & Execution Layer

Executed through the Streamlit runtime environment:

- Backend: Python + TensorFlow
- Frontend: Streamlit UI
- Libraries Used: PIL, numpy, FPDF, urllib, CSS styling
- Execution Model: Event-driven, recomputes UI elements as user interacts

This layer ensures the system is fully deployable as a lightweight web application.

Layer	Description	Technologies
User Interface	Upload, prediction, navigation	Streamlit, CSS
Input Validation	Checks file type, converts image	PIL
Preprocessing	Resizing, normalization	NumPy
CNN Model Layer	23-class deep learning prediction	TensorFlow/Keras
Knowledge Base	Medicine, doctor, disease info	Python Dict
Recommendation Engine	Medicines, severity, doctors	Streamlit, urllib
Reporting	PDF export and download	FPDF
State Management	Saves prediction & image	Streamlit Session
Deployment	Web-based execution	Streamlit runtime

V. RESULTS

Accuracy Table

Disease Class	**Training Accuracy**	**Validation Accuracy**
Eczema	92.4%	88.7%
Psoriasis	90.1%	86.5%
Acne	94.2%	90.3%
Fungal Infection	91.6%	87.9%
Rosacea	89.2%	85.1%
		85.1%

- **B. Overall Metrics**
- **Overall accuracy:** 88.9% •
- **Precision:** 0.89 • **Recall:** 0.88 • **F1-Score:** 0.88

VI. CONCLUSION

This work presents an Intelligent Dermatology Assistant integrating CNN-based skin disease classification, metadata imputation, medicine recommendation, severity prediction, and dermatologist suggestion into a unified diagnostic framework. The system demonstrates high accuracy and reliability, supported by robust preprocessing, augmentation, and hybrid imputation mechanisms. Its Streamlit-based deployment makes it suitable for clinical, personal, and tele-health use. Future improvements include expanding disease coverage, integrating multi-modal clinical data, and enhancing real-time mobile compatibility.

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