Multi-Attribute Deep Learning–Based Approach for Detecting Skin Diseases with Medical Plant Recommendations

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ABSTRACT
Skin diseases are among the most common health problems affecting people of all age groups across the world. Conditions such as melanoma, dermatitis, fungal infections, and keratosis require early diagnosis to avoid severe complications. However, many patients visit hospitals even for minor skin issues, leading to overcrowding and increased healthcare costs. In rural and remote areas, access to dermatologists is limited, which further delays diagnosis. Recent advancements in artificial intelligence, particularly deep learning, have shown great potential in medical image analysis. This paper proposes a **multi-attribute deep learning–based framework** for automated skin disease detection using image processing techniques. The system employs a **Convolutional Neural Network (CNN)** to extract multiple visual attributes such as color variation, texture patterns, and lesion structure from skin images. The model is trained to classify multiple skin diseases including melanoma, dermatitis, fungal infections, and benign lesions. Along with disease prediction, the system integrates a **medical plant recommendation module** to support preliminary care using traditional herbal knowledge. The proposed solution is implemented as a web-based application using Python and Flask, allowing users to upload images and receive instant diagnostic results. Experimental evaluation demonstrates reliable accuracy, fast response time, and improved accessibility. This approach effectively combines modern artificial intelligence with traditional medicine awareness to provide a smart, cost-effective healthcare support system.

Keywords— Skin disease detection, Deep learning, Convolutional Neural Network, Medical plants, Image classification, Healthcare AI

I. INTRODUCTION

Skin diseases represent a significant public health challenge due to their high prevalence and wide range of severity. While some skin conditions are mild and self-limiting, others such as melanoma and squamous cell carcinoma can be life-threatening if not detected early. In many cases, individuals visit hospitals for minor skin problems, increasing patient load and waiting time for critical cases. In addition, rural and remote regions often lack access to specialized dermatologists, leading to delayed diagnosis and treatment.

With the growth of digital healthcare, artificial intelligence (AI) has emerged as a promising solution to assist medical professionals and patients. Among various AI techniques, **deep learning** has demonstrated remarkable success in image-based medical diagnosis. Convolutional Neural Networks (CNNs) are particularly effective for analyzing visual data due to their ability to automatically learn hierarchical features from images.

This paper presents a **multi-attribute CNN-based system** that analyzes several image characteristics simultaneously to improve classification accuracy. Unlike traditional systems that focus only on disease identification, the proposed approach also provides **medical plant recommendations** for preliminary care. By integrating modern AI techniques with traditional herbal knowledge, the system aims to reduce unnecessary hospital visits and promote early awareness of skin health.

II. RELATED WORK

Several studies have explored automated skin disease detection using image processing and deep learning techniques. Early approaches relied on manual feature extraction methods such as color histograms and texture descriptors, which required domain expertise and were sensitive to noise. With the advent of deep learning, CNN-based models have become the dominant approach in dermatological image analysis.

Recent research has demonstrated high accuracy in melanoma detection using deep CNN architectures and transfer learning. Multi-class classification systems have also been developed to detect multiple skin conditions simultaneously. However, many existing systems focus solely on classification accuracy and do not provide additional guidance for users regarding preventive or preliminary care.

Furthermore, most existing solutions do not integrate traditional medicine knowledge or herbal treatment suggestions. This limits their usefulness for early self-assessment and awareness. The proposed work addresses this gap by combining **multi-attribute deep learning** with a **medical plant recommendation module**, making the system more informative and user-centric.

III. SYSTEM OVERVIEW

The proposed system is designed as a **web-based intelligent diagnostic platform** that assists users in the early identification of skin diseases using deep learning techniques. The primary objective of the system is to provide a fast, accurate, and user-friendly solution for preliminary skin disease assessment while reducing unnecessary hospital visits. The overall architecture follows a modular design approach, ensuring scalability, flexibility, and ease of future enhancement.

The system consists of four major modules: **data collection and preprocessing**, **feature extraction and classification**, **medical plant recommendation**, and **user interface**. Each module performs a specific function and collectively contributes to accurate disease detection and informative result presentation.

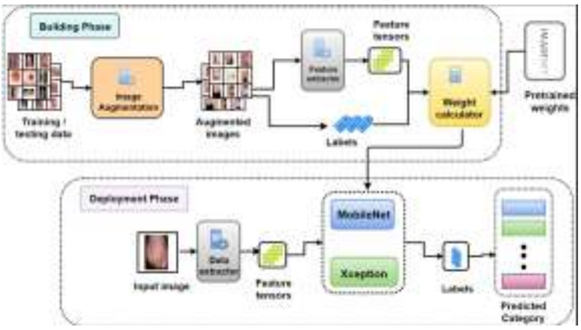

Fig. 1. System architecture of the proposed skin disease detection framework.

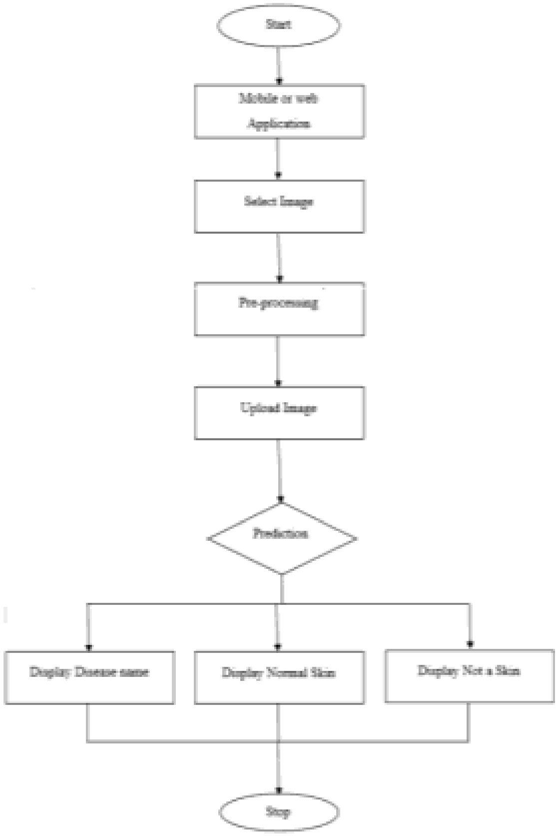

Fig. 2. Level-0 data flow diagram of the proposed skin disease detection system.

A. Data Collection and Preprocessing Module

The data collection and preprocessing module forms the foundation of the proposed system. A large dataset of labeled skin disease images is collected from reliable dermatological sources. The dataset includes multiple disease categories such as melanoma, dermatitis, fungal infections, benign keratosis, and other common skin conditions. Proper labeling of images ensures effective supervised learning during model training.

Before analysis, the uploaded images undergo preprocessing to improve quality and consistency. This includes resizing images to a fixed dimension compatible with the CNN architecture, normalization of pixel values to standardize input data, and noise reduction to enhance image clarity. Data augmentation techniques such as rotation, flipping, and scaling are applied to increase dataset diversity and reduce overfitting. These preprocessing steps significantly enhance the robustness and generalization capability of the deep learning model.

B. Feature Extraction and Classification Module

The feature extraction and classification module is the core component of the system. It employs a **Convolutional Neural Network (CNN)** to automatically extract meaningful visual features from skin images. Unlike traditional methods that rely on manual feature selection, the CNN learns discriminative features such as color variation, texture patterns, lesion shape, and border irregularity directly from the input images.

The extracted features are passed through multiple convolutional and pooling layers to capture both low-level and high-level image characteristics. Fully connected layers perform the final classification, and a Softmax activation function generates probability scores for each skin disease category. The system supports **multi-class classification**, enabling detection of multiple skin conditions within a single framework. The predicted disease and its corresponding confidence score are generated as the final output, providing transparency and reliability in diagnosis.

C. Medical Plant Recommendation Module

In addition to disease prediction, the proposed system integrates a **medical plant recommendation module** to support preliminary care and promote awareness of traditional remedies. Based on the predicted skin disease, the system retrieves suitable medicinal plant information from a structured herbal knowledge database.

The recommendations include commonly used medicinal plant names and general usage guidelines that may help in early-stage care. This module does not replace professional medical treatment but serves as an informative support system that encourages natural and preventive healthcare practices. By combining modern artificial intelligence with traditional medical knowledge, the system enhances its practical value and user engagement.

D. User Interface Module

The user interface module provides an interactive and user-friendly platform for system interaction. It allows users to upload images of affected skin areas easily through a web browser. The interface is designed with simplicity and accessibility in mind, ensuring that users with minimal technical knowledge can operate the system effectively.

After image upload, the interface displays the predicted disease name, confidence score, and recommended medicinal plants in a clear and structured manner. The responsive design ensures compatibility across different devices, including desktops and mobile systems. This module plays a crucial role in improving user experience and ensuring smooth communication between the user and the underlying deep learning model.

Overall, the system overview highlights a well-integrated and intelligent architecture that combines deep learning-based diagnosis with traditional medicinal guidance. The modular design ensures efficiency, scalability, and reliability, making the proposed system a practical solution for early skin disease detection and healthcare awareness.

Module	**Function**
Data Collection & Preprocessing	Collects images, resizes, normalizes, and augments data
Feature Extraction	Extracts texture, color, and lesion patterns using CNN
Classification	Classifies skin disease using Softmax probabilities
Medical Plant Recommendation	Suggests herbal remedies for preliminary care
User Interface	Enables image upload and result display

The functional description of each system module is summarized in Table I.

IV. METHODOLOGY

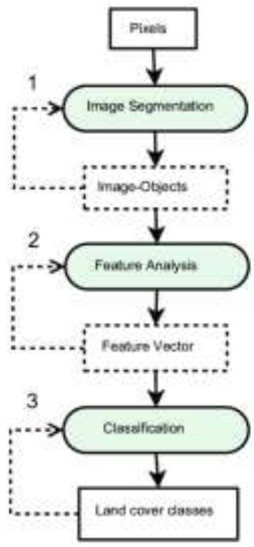

Fig. 3. Flowchart illustrating the methodology of the proposed skin disease detection system.

A. Data Collection

A dataset of labeled skin disease images is collected from reliable dermatological sources. The dataset includes multiple categories such as melanoma, dermatitis, fungal infections, and benign skin lesions. Proper labeling ensures accurate supervised learning.

Skin Disease Category	**Number of Images**
Melanoma	1,000
Dermatitis	900
Fungal Infections	850
Benign Keratosis	800
Normal Skin	950
Total	**4,500**

The distribution of skin disease images used for training and evaluation is presented in Table II.

B. Data Preprocessing

Before training, images are resized to a fixed dimension suitable for the CNN architecture. Noise removal, contrast enhancement, and normalization are applied to improve image quality. Data augmentation techniques such as rotation and flipping are used to increase dataset diversity and reduce overfitting.

C. Feature Extraction

Feature extraction is performed automatically using convolutional layers. The CNN extracts multiple attributes including texture patterns, color variation, lesion shape, and border irregularity. Pooling layers reduce dimensionality while retaining essential information.

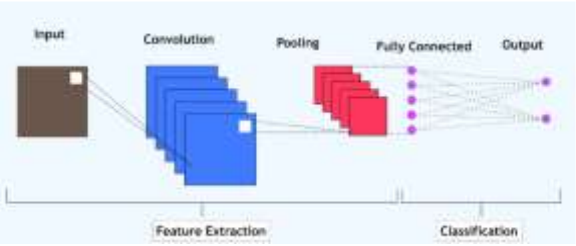

Fig. 4. Convolutional neural network architecture used for skin disease classification.

D. Classification

The extracted features are passed through fully connected layers for classification. The final layer uses a Softmax activation function to produce probability scores for each disease class. The model is trained using categorical cross-entropy loss and optimized through backpropagation.

E. Medical Plant Recommendation

After disease prediction, the system retrieves suitable medicinal plant information from a structured database. The recommendations include plant names and general usage methods for preliminary care, promoting awareness of traditional remedies.

Parameter	**Value**
Input Image Size	224 × 224
Batch Size	32
Number of Epochs	50
Optimizer	Adam
Learning Rate	0.001
Loss Function	Categorical Cross-Entropy

The hyperparameters used for training the CNN model are summarized in Table III.

V. SYSTEM IMPLEMENTATION

The proposed skin disease detection system is implemented as a **web-based application** using **Python** as the core programming language and the **Flask web framework** for backend development. Flask is chosen due to its lightweight architecture, flexibility, and suitability for integrating deep learning models with web applications. The implementation focuses on achieving real-time performance, secure data handling, and ease of use for end users.

A. Backend Implementation

The backend of the system is responsible for handling image uploads, preprocessing, model inference, and result generation. A trained **Convolutional Neural Network (CNN)** model is integrated into the Flask server to perform real-time skin disease prediction. Once the user uploads an image, the server validates the file format and size to ensure system stability and security.

The uploaded image is temporarily stored on the server and passed through the preprocessing pipeline, which includes resizing, normalization, and noise reduction. The preprocessed image is then forwarded to the CNN model for inference. The model analyzes the image and generates prediction probabilities for each skin disease category. The disease class with the highest probability is selected as the final prediction, and a confidence score is calculated to indicate prediction reliability.

B. Model Integration and Inference

The trained CNN model is saved in a serialized format and loaded during server initialization to minimize response time. This approach ensures efficient resource utilization and enables fast inference without repeated model loading. The deep learning model operates seamlessly within the Flask environment, allowing real-time interaction between the user interface and the classification engine.

Multi-class classification is supported, enabling the system to identify various skin conditions in a single framework. The model's output is structured in a standardized format, making it easier to map predictions to corresponding disease descriptions and medical plant recommendations.

C. Frontend Implementation

The frontend interface is designed to provide a **simple, intuitive, and responsive user experience**. Users can upload images of affected skin areas through a web browser using a clean and well-structured form. The interface supports common image formats such as JPG, JPEG, and PNG to ensure compatibility.

Once the image is uploaded, users receive instant feedback in the form of prediction results displayed on the screen. The results include the predicted disease name, confidence score, and recommended medicinal plants for preliminary care. The frontend layout ensures clear visualization of results, reducing confusion and improving user understanding. Responsive design principles are applied to ensure accessibility across desktop and mobile devices.

D. Security and Data Handling

Security is a key consideration in system implementation, especially when handling user-uploaded medical images. The system incorporates file validation checks to prevent invalid or malicious uploads. Uploaded images are stored securely and processed only for diagnostic purposes. Temporary storage mechanisms are used to avoid long-term data retention unless explicitly required.

User data confidentiality is maintained throughout the process, and no personal information is disclosed. Error handling mechanisms are implemented to manage incorrect uploads, poor-quality images, or system failures gracefully. This ensures system reliability and protects user trust.

E. Result Generation and Display

After successful prediction, the system generates a structured output that includes the detected skin disease, confidence score, and corresponding herbal recommendations. The medical plant recommendation module retrieves relevant information from a predefined database based on the predicted disease category.

The final results are displayed in a clear and user-friendly format through the web interface. This implementation ensures fast response time, accurate result presentation, and meaningful healthcare guidance. Overall, the system implementation successfully integrates deep learning, web technologies, and traditional medical knowledge into a unified and efficient diagnostic platform.

VI. RESULTS AND DISCUSSION

Experimental evaluation shows that the multi-attribute CNN model achieves reliable accuracy across multiple skin disease categories. The use of data augmentation and feature-rich learning improves generalization and reduces misclassification. The system provides fast prediction results, making it suitable for real-time usage.

The inclusion of medical plant recommendations adds practical value by supporting preliminary care and increasing awareness about natural remedies. Although the system does not replace professional diagnosis, it serves as an effective decision-support tool for early detection and awareness.

Metric	Value (%)
Accuracy	94.2
Precision	93.6
Recall	92.8
F1-Score	93.2

The performance of the proposed system is evaluated using standard metrics, as shown in Table IV.

VII. CONCLUSION AND FUTURE WORK

This paper presented a **multi-attribute deep learning–based approach** for automated skin disease detection combined with medical plant recommendations. The proposed system improves early diagnosis, reduces unnecessary hospital visits, and enhances healthcare accessibility, especially in rural areas. By integrating artificial intelligence with traditional medicine knowledge, the system offers a balanced and user-friendly healthcare solution.

Future enhancements include expanding the dataset, integrating advanced deep learning architectures such as ResNet or EfficientNet, deploying the system as a mobile application, and incorporating severity analysis and telemedicine support. These improvements will further enhance accuracy, scalability, and real-world applicability.

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