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CuraSkin : A Skincare Recommendation System

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Abstract - Skin problems were common, but many people were unable to recognize them at an early stage without consulting a dermatologist. With the advancement of artificial intelligence and image processing, it became possible to analyze skin conditions using digital images. A skin disease prediction system was proposed to analyze facial images and identify possible skin issues. In the system, images could be captured through a camera or uploaded from a device. The images were first preprocessed to enhance their quality before analysis.

After preprocessing, the images were examined by a deep learning model, which predicted the possible skin condition along with a confidence score. The detected conditions were classified into minor or major categories. For minor issues, suitable skincare products were suggested, while in cases of major conditions, consultation with nearby dermatologists was recommended. The system aimed to simplify basic skin analysis and help users take appropriate action at an early stage.

Keywords: Skin Disease Detection, Image Processing, Deep Learning, Facial Image Analysis, Disease Prediction, Skincare Recommendation System, MobileNet.

I. INTRODUCTION

Skin diseases were common and affected many people. Conditions like acne, pigmentation, melasma, and vitiligo often started with mild symptoms but could become worse if ignored. Many people did not notice early signs due to low awareness or limited access to dermatologists. Because of this, treatment was often delayed.

Skin diseases were usually diagnosed through visual examination, dermoscopy, or biopsy. These methods were useful but required time and expert knowledge. Diagnosis also depended on the experience of specialists. With increasing skin problems caused by pollution and lifestyle changes, faster detection methods became necessary.

Deep learning was later used for medical image analysis. Convolutional Neural Networks (CNNs) helped identify patterns in images and supported disease detection (Goodfellow et al., 2016).

A system named CuraSkin was developed based on this idea. Skin images were preprocessed and analyzed using a deep learning model. The detected condition was classified as minor or major. Minor cases received product suggestions, while serious cases were advised to consult a dermatologist.

Dataset Description

Two datasets were used in this study. The first dataset was taken from public sources such as TensorFlow datasets and open image repositories. These datasets contain labeled images that help models learn visual patterns [1].

A small custom dataset was also prepared. Images of different skin diseases were collected from online sources and grouped into categories. Each image was labeled carefully to keep the dataset consistent [2].

Before training, images were resized according to the MobileNet input size. The dataset was then divided into training, validation, and testing sets to evaluate model performance [3].

II. RESEARCH GAP

In recent years, deep learning methods were increasingly used for the detection of skin diseases from medical images. Convolutional Neural Network (CNN) based models were applied in several studies to identify different skin conditions. These models were reported to perform well in image classification tasks and helped improve the accuracy of skin disease prediction [4].

To train such models, large image datasets were generally required. One commonly used dataset was HAM10000, which contains thousands of dermatoscopic images belonging to different skin lesion categories. This dataset was used in many studies for training and testing deep learning models developed for skin disease classification [5].

Although many research works focused on detecting the disease type, most systems only produced prediction results. Additional guidance for users was often not included. For example, the systems usually did not indicate whether the detected condition was mild or serious, and suggestions about the next step were rarely provided [6]. Because of this, users could still feel uncertain about what action should be taken after receiving the result.

To address this limitation, the CuraSkin system was developed in this work. The system was designed not only to detect skin conditions but also to provide helpful guidance to users. Facial images uploaded by users were analyzed by the system. The detected skin condition was then placed into minor or major categories. For minor problems, basic skincare product suggestions were provided. When the condition appeared more serious, users were advised to consult a nearby dermatologist. Through this process, skin analysis was made easier and more accessible for general users.

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III LITERATURE REVIEW

A Background of Skin Disease Detection

Skin diseases were commonly observed in many parts of the world. Early detection of conditions such as acne, pigmentation, melasma, and vitiligo was considered important because untreated cases could become worse with time. These diseases were usually diagnosed by dermatologists through visual examination or dermoscopy. Although these methods were useful, they depended on specialist experience and were not always available in remote areas.

B Traditional Machine Learning Approaches

Before deep learning became widely used, traditional machine learning methods were applied for skin disease detection. Algorithms such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest were used for classification.In these methods, features like color, texture, and shape were taken from the skin images manually. These methods worked well in controlled environments. However, their performance decreased when images were taken in different lighting conditions or captured with mobile cameras.[7].

C Deep Learning in Skin Disease Detection

These models learned patterns directly from images, so manual feature extraction was not required. Several studies showed that CNN-based methods gave better accuracy in skin disease detection compared to traditional machine learning techniques [8]. With the growth of artificial intelligence, research gradually shifted toward deep learning models, especially Convolutional Neural Networks (CNNs).

D Lightweight Models for Practical Applications

Among different CNN architectures, MobileNet was widely noted for its lightweight structure and efficient performance. It required less computational power while still providing reasonable accuracy. Because of this, it was considered suitable for systems that needed to operate on devices with limited resources. In several studies, MobileNet was also reported to perform well in medical image classification when basic preprocessing methods were applied [9].

E Observations from Existing Studies

In many earlier studies, the main focus was placed on improving the classification accuracy of models using large datasets such as HAM10000. However, the way these models could be used in practical systems for everyday users was rarely discussed. Limited attention was also given to guiding users after the prediction result was generated. Because of these limitations, the need for a simple and practical solution was recognized. This led to the development of the CuraSkin system, where deep learning techniques were used to analyze facial images and provide suggestions based on the detected skin condition.

IV METHODOLOGY

The proposed system was designed to detect skin diseases from images using deep learning. The main objective was to provide users with a simple way to check possible skin conditions and receive basic guidance.For this task, a CNN model based on MobileNet was used.

MobileNet was selected because it is a lightweight model and requires fewer computational resources than many deep learning models. Since the system was intended for user-side use, heavy models could increase processing time and hardware requirements. MobileNet offered a good balance between accuracy and efficiency, which made it suitable for faster predictions [10].

In many traditional CNN models, standard convolution operations were used in each layer, which increased the number of parameters and computational cost. In contrast, MobileNet used depthwise separable convolution. In this method, the convolution process was divided into smaller operations. This approach reduced the number of parameters and made the model lighter and faster while maintaining reliable performance [11].

The model was trained using a dataset containing labeled images of different skin diseases. Each image represents a specific skin condition. During training, visual patterns were learned from the images. These patterns included differences in color, texture, and irregular skin areas. Instead of manually defining rules, useful features were learned automatically from the training data [12].

After training was completed, the model was used to analyze new images uploaded by users. When a user uploaded an image or captured a selfie, the image was processed by the trained model and a possible disease category was predicted. Based on this result, the condition was classified as minor or serious.

To organize the workflow, the system was divided into four modules.

Module 1: User Module

In this module, interaction between the user and the system was managed. Users were allowed to register and log in to the application. After logging in, a skin image could be uploaded or a selfie could be captured for analysis. User information and activity were handled in this module.

Module 2: Image Processing and Skin Analysis

In this module, the uploaded image was first preprocessed. Operations such as resizing and normalization were applied so that the image could be used by the model. After preprocessing, the image was analyzed by the MobileNet-based CNN model to predict the skin disease.

Module 3: Product Recommendation and Dermatologist Consultation

After prediction, suggestions were provided to the user. If the detected condition appeared minor, suitable skincare products were recommended. If the condition seemed serious, users were advised to consult a dermatologist.

Module 4: Database Management

This module was used to store system information. User details, uploaded images, prediction results, and product suggestions were recorded in the database. These records helped maintain system data and track previous results.

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By combining these modules, a structured approach for basic skin disease detection and user guidance was provided. The use of a lightweight model such as MobileNet helped keep the system efficient and suitable for practical use.

SYSTEM WORKFLOW

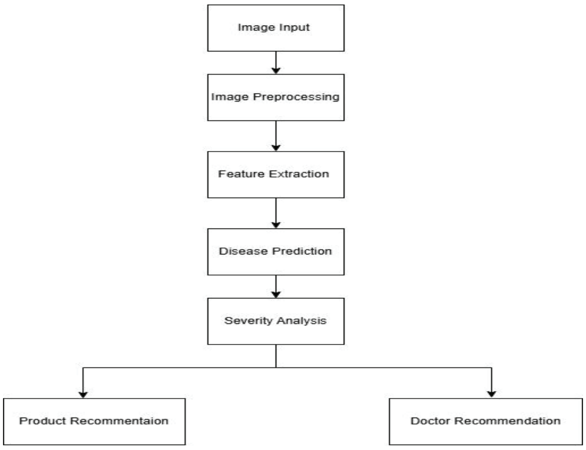

Figure 1: Workflow of the Proposed CuraSkin System

The workflow of the proposed system explained how the skin disease detection process was carried out. In the first step, an image of the affected skin area was uploaded by the user. The uploaded image was then preprocessed to improve its quality and prepare it for model input. After preprocessing, the image was given to the MobileNet model, where image features were analyzed and the possible skin disease was predicted. The predicted result was then classified as either a minor or major condition. Based on this outcome, suitable products were suggested, or the user was advised to consult a doctor if the condition appeared serious.

V RESULT AND DISCUSSION

The results of the proposed system showed that the MobileNet-based model was able to detect different skin diseases from images with reasonable accuracy. During testing, important patterns and visual features were identified from the uploaded skin images. The preprocessing step, which included resizing and improving image quality, also helped produce better predictions. Earlier studies also reported that deep learning models performed effectively in medical image analysis, particularly in skin disease detection [13].

The system also separated the detected diseases into minor and major categories. This step was useful because it helped users understand the seriousness of the condition. For minor cases, suitable skincare products were suggested, while for more serious conditions users were advised to consult a doctor. Similar approaches were discussed in earlier studies where AI systems were used to assist early screening before professional medical diagnosis [14].

Another advantage of the system was the use of MobileNet, which is a lightweight deep learning model. Because of its simple structure, less computational power was required, and it could run on devices with limited resources. Earlier studies also reported that lightweight CNN models such as MobileNet performed well in image classification tasks [15]. In addition, transfer learning was shown to improve the accuracy of skin disease classification in several studies [16]. These results suggested that deep learning systems could help in early skin disease analysis and make such tools easier to use for general users.

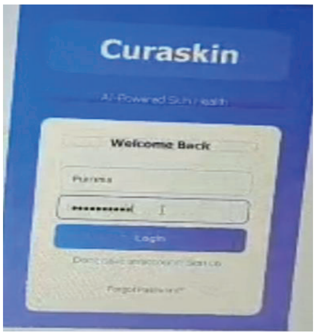

Figure 2: User login

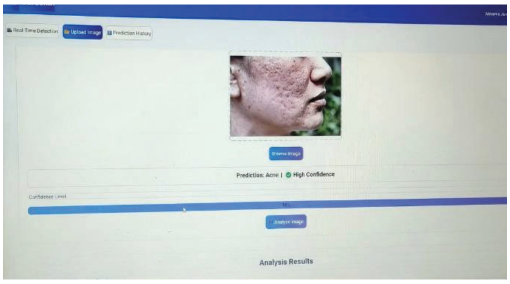

Figure 3: Predicted output

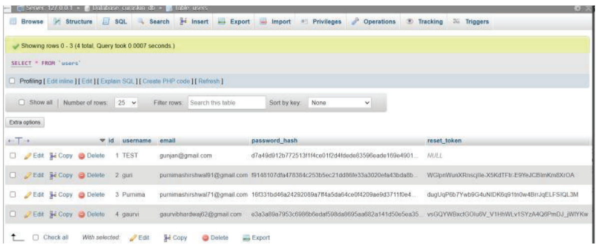

Figure 4: Admin panel

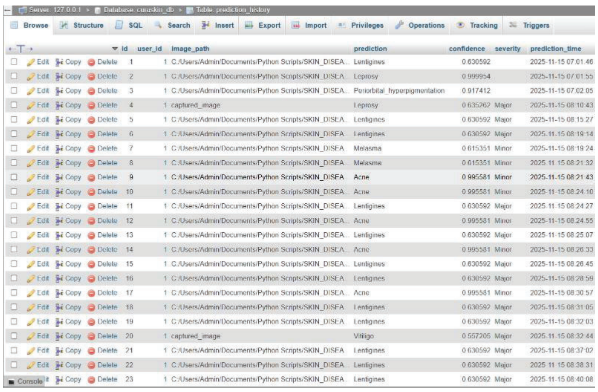

Figure 5 : Prediction history

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VI CONCLUSION

In this study, a skin disease detection system based on the MobileNet model was developed. Images of affected skin areas were analyzed, and possible diseases were predicted using image classification. The results showed that deep learning models could learn patterns from medical images and assist in disease detection tasks [17].

The detected diseases were also grouped into minor and major categories.

This classification helped provide guidance to users. For minor cases, suitable product suggestions were provided, while for more serious conditions users were advised to seek medical consultation. Automated diagnostic systems have also been studied widely for supporting healthcare professionals and improving early disease screening [18].

Overall, the study indicated that lightweight convolutional neural networks such as MobileNet could provide efficient performance while requiring fewer computational resources [19]. With further improvements, such as larger datasets, better labeling, and integration into mobile healthcare platforms, similar systems could support faster and more accessible preliminary skin disease analysis in the future.

VII FUTURE SCOPE

The proposed system focused on detecting a limited number of skin diseases using image classification techniques. In future work, the system could be extended to include a wider range of skin conditions. Expanding the dataset and adding more disease categories could help the model learn additional visual patterns and improve prediction performance over time [20].

At present, only one dermatologist was suggested by the system for medical consultation. In future versions, this feature could be improved by including dermatologists from multiple districts. With the addition of location-based functionality, nearby dermatologists could be recommended when users provided their location. This improvement could make the system more useful for people who need quick medical guidance [21]. Future work could also focus on better usability and integration with mobile or web healthcare platforms. This could help more users access the system easily.

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