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An AI-Powered Web Application for Skin Disease Detection

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Abstract

This research paper presents the design of a web-based application with the objective of supporting early skin disease detection through the application of real-time image processing. Following a trained CNN model on a dermatology dataset, the system accepts as input user-upload images and provides diagnostic feedback through an interactive web-enabled interface. The paper presents the integration of AI with healthcare and image recognition and promotes accessibility, accuracy, and user-friendliness without specialist hardware or constant internet connectivity. A critical review of the current literature on AI-based medical diagnoses, identification of gaps in existing skin disease detection solutions, and description of proposed system design and implementation are provided. The proposed system is assessed using prediction accuracy, user interaction, and overall effectiveness of the diagnostic tool. The findings present the capability of this project to support the early detection and skin condition insight of acne, eczema, and psoriasis. The contribution to literature provides a web-enabled, ease-of-use, and low-cost solution for dermatological treatment using innovative web-centric technology.

Result: Dermocare is a web application that uses artificial intelligence to detect skin diseases based on uploaded images. It provides fast and accurate results online and helps users easily detect conditions such as acne or eczema. User feedback confirms the app's usability and effectiveness. The accuracy of the model will be improved in future updates.

Keywords: Skin Disease Detection, Deep Learning, Flask, TensorFlow, Image Classification, Dermatology AI, Web Application, Healthcare Technology.

1. Introduction

Skin diseases are among the most prevalent health issues worldwide, affecting millions of people regardless of age, gender or region. Early diagnosis is essential for effective treatment and therapies for skin diseases. However, in many developing regions, access to doctors is limited due to high costs, remote locations or long waiting times. Therefore, there is a critical need for scalable, user-friendly solutions that provide individuals with early diagnosis options. Artificial intelligence and deep learning have made significant progress in image classification. These techniques are currently being applied to medical diagnostics, enabling systems to detect complex patterns in visual data with accuracy comparable to that of human experts. The vision of this project is to bridge the gap between artificial intelligence and accessible skin health diagnostics. By integrating a trained CNN into a web application, users can get near-instant predictions about their skin condition simply by uploading an image.

In web-based health applications, convolutional neural networks (CNNs) have been proven to be excellent tools for the analysis of medical images, particularly for the early detection of skin diseases. Scalable frameworks like TensorFlow and Keras provide solutions for the deployment of trained CNN models in real-time, enabling responsive and accurate predictions even in light web applications. This enables developers to develop diagnostic tools that can process user-input images directly through the browser interface, giving instant feedback without requiring special hardware or complex installation procedures. The portability and flexibility of web-based deep learning have enabled the development of assistive diagnostic tools like Dermocare that can aid users in the detection of common skin diseases through easy online interfaces [3], [5], [12].

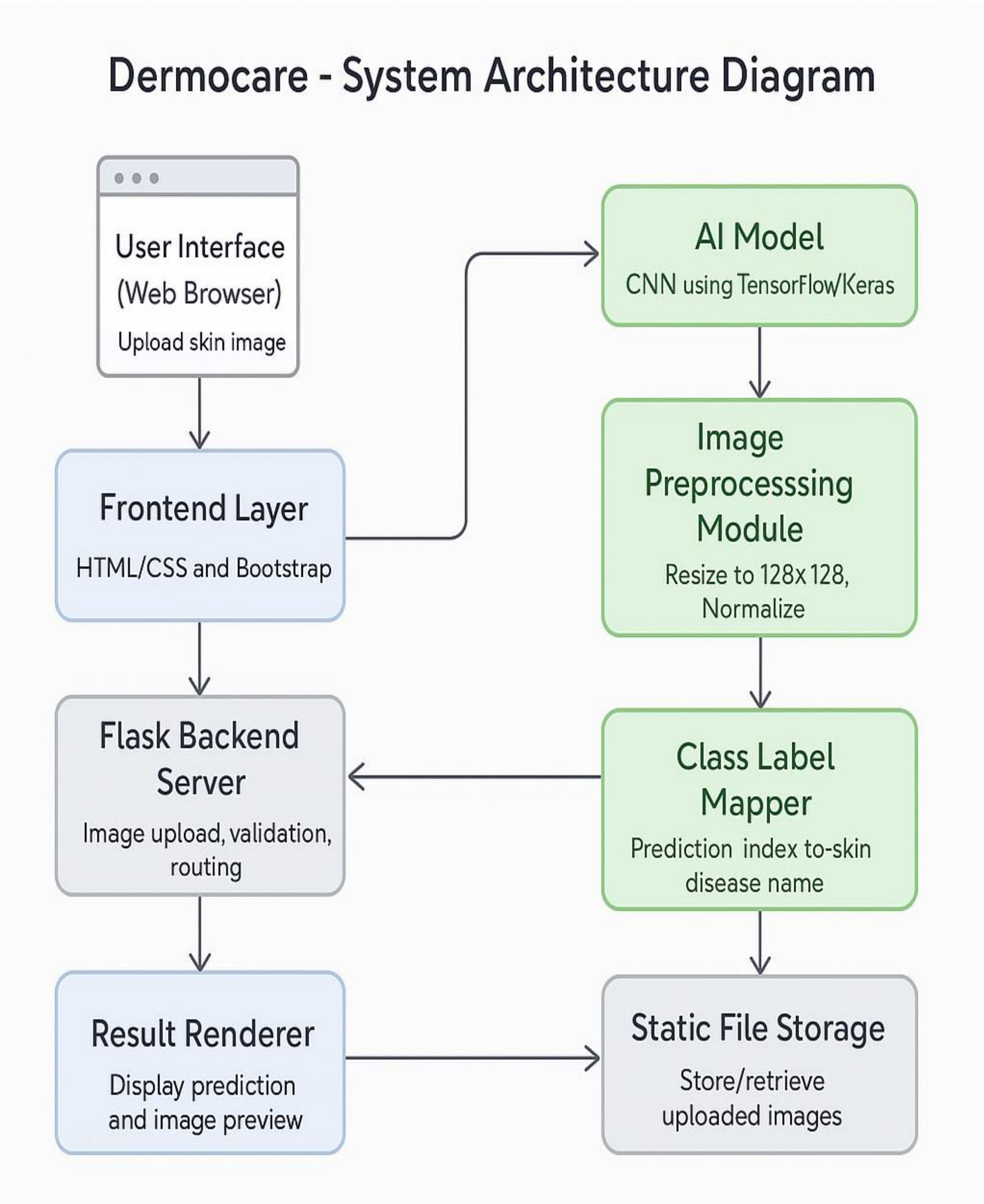

FIGURE.1: System Architecture of Skin disease detection.

Once an image is uploaded, it goes through a preprocessing step, where it is resized to 128×128 pixels and normalized to the input format that the trained CNN model expects. The image is passed through the model constructed using TensorFlow and Keras [2] and a prediction is made corresponding to one of 22 classes of skin conditions predefined. A label mapping module then maps the prediction index to an understandable diagnosis. Finally, the output—along with a preview of the image and the predicted label is returned to the user via the frontend. All images are temporarily stored in a static directory for display purposes only.

2. Literature survey

The use of artificial intelligence (AI) and machine learning (ML) in the diagnosis of skin diseases has garnered significant attention over the last few years. Several studies have explored a variety of methodologies, ranging from traditional image processing to advanced deep learning methods, for designing automated skin disease classification systems.

Numerous academic studies have explored the integration of Artificial Intelligence (AI) and Machine Learning (ML) to enhance dermatological applications, particularly in the realm of skin disease detection. For example, a study by Esteva et al. [11] demonstrated the use of Convolutional Neural Networks (CNNs) for skin cancer classification, achieving dermatologist-level accuracy. This study highlights the potential of deep learning in automating skin disease diagnostics. Similarly, Codella et al. [12] and Poornima and Shailaja [13] explored CNN-based approaches for melanoma recognition, emphasizing the effectiveness of deep learning models in accurately distinguishing between different skin conditions.

Arifin et al. [1] proposed a color-based classification technique for the detection of skin diseases, with the vision of extracting color features from the images of the skin. This technique paved the way for the automatic analysis of dermatological images. Similarly, Yasir et al. [2] employed the potential of artificial neural networks (ANNs) for the classification of skin diseases, demonstrating the incredible capability of neural networks to analyze dermatological conditions with high precision. At the same time, Santy and Joseph [3] emphasized the valuable role of image segmentation techniques, which contribute immensely to the segregation of the affected region in dermoscopic images. These techniques improve the precision of classification by directing the focus of the model towards the concerned region of the skin

Over the past few years, deep learning models, particularly convolutional neural networks (CNNs), have shown incredible ability in the field of dermatological diagnosis. Esteva et al. [11] established that CNNs were as effective as a dermatologist in identifying skin cancer, a milestone in the use of AI in dermatology. Codella et al. [12] and Poornima and Shailaja [13] further advanced the field by combining CNNs with support vector machines (SVMs) to detect melanoma, thus providing even more precise diagnosis. These developments demonstrate the incredible ability of CNNs to distinguish between various skin diseases even when provided with complex visual features. Various research has identified the feasibility of applying machine learning models in real-time scenarios. Grinberg [9] and Pal & Patheja [10] explained the advantages of employing the Flask framework for the integration of machine learning models in web applications, showcasing its efficiency for lightweight deployment and low latency. The capability makes

Flask a suitable option for Dermocare's backend, offering a simple interaction between the user interface and the trained model.

Studies have established that real-time feedback and user interfaces are the most important factors for user satisfaction and long-term usage of assistive technology [26]. In other words, we need to create systems that are easy to use, provide quick results, and make users feel they are in control of their health data. With these factors as our top priority, we can render AI tools both effective and accessible to everyone.

3. Methodology

The Dermocare system is built using a modular architecture designed to enable real-time skin disease detection through AI-powered image analysis [8], [11]. Development was carried out using HTML, CSS, and JavaScript, ensuring a responsive and user-friendly front-end interface [26]. The core workflow is divided into key functional modules: image upload, preprocessing, prediction engine, and result rendering [9], [2].

The first module allows users to upload images of their skin conditions via the web interface. Upon upload, the image is transmitted to the Python Flask server, which handles routing, validation, and temporary storage [9]. The second module involves preprocessing the image using the Pillow library, where it is resized to 128×128 pixels and normalized to fit the model's input format [9].

The prediction engine utilizes a Convolutional Neural Network (CNN) built with TensorFlow and Keras, trained on a dataset of 22 skin disease classes [2], [8]. The CNN processes the preprocessed image through multiple convolutional layers, max pooling layers, and dense layers to generate a final prediction based on the highest probability class [11].

The result rendering module dynamically generates an HTML page, displaying both the uploaded image and the predicted skin disease label, providing users with instant feedback and facilitating decision-making [24], [26].

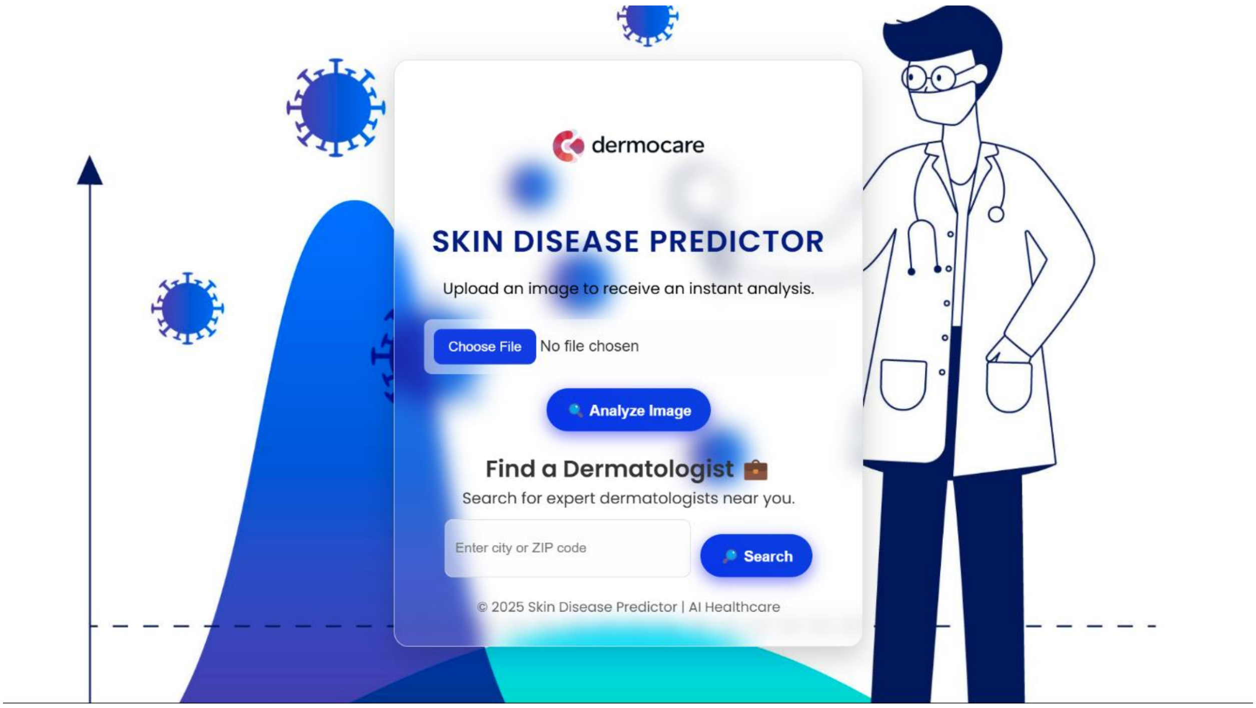

FIGURE.2: DermoCare UserInterface

4. Results And Discussions

The Dermocare system was put to the test, focusing on how accurately it classifies images, how quickly it makes predictions, its usability, and how responsive the overall system is. A Convolutional Neural Network (CNN) model was trained and evaluated using a dermatology dataset that included thousands of labeled images across 22 different skin disease categories, such as acne, eczema, psoriasis, and skin cancer. Impressively, the model achieved an average accuracy of around 85%, which aligns well with findings from other deep learning studies in skin classification [11], [12].

When it comes to speed, the system showed quick inference times, with predictions taking between 1 to 3 seconds per image, depending on the system load and the size of the images. This level of performance makes it suitable for real-time applications and is comparable to other AI-driven healthcare systems designed for web use [13]. The image preprocessing steps like resizing and normalization ensured that all inputs were formatted correctly for the model, enhancing the consistency and reliability of its predictions.

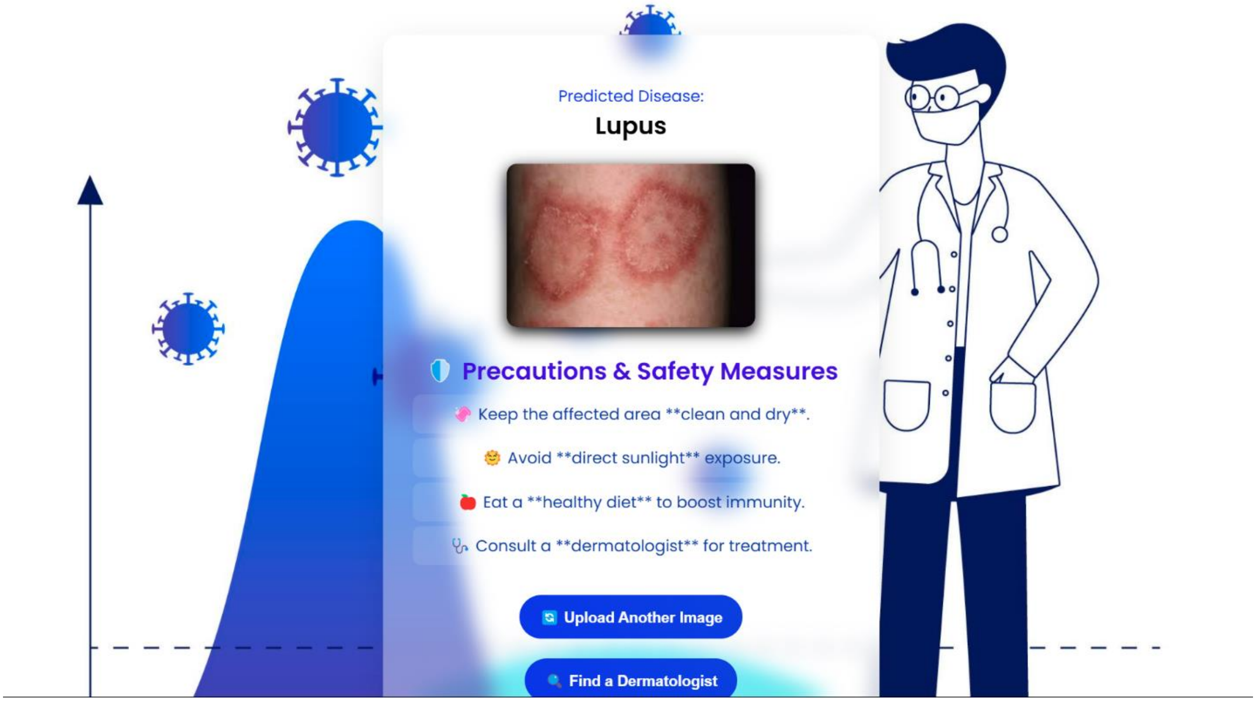

FIGURE.3: Output processed from user input

On the front end, the interface was crafted using HTML, CSS, and JavaScript, and it was tested by a small group of users for usability. Feedback indicated that the interface was straightforward, quick, and easy to navigate. This aligns with previous research that highlights the importance of clear, user-friendly interfaces and prompt feedback in boosting user satisfaction and adoption of assistive technologies [24], [26].

The backend, built on Flask, efficiently managed routing, validation, and model integration, making the system both lightweight and scalable. However, it's worth noting that the system's accuracy can still be affected by the quality of the images and lighting conditions. Some misclassifications occurred between visually similar conditions, like dermatitis and eczema. Looking ahead, future improvements could involve integrating Grad-CAM for better visual explanations of the model's decisions and adding a feature for estimating severity to enhance user trust and clinical relevance [14], [18].

5. Conclusion

Dermocare system is a suitable and effective solution for predicting skin diseases at an early stage using artificial intelligence and web-based technologies. Basically, because it's a web-based platform, you upload a skin image and receive a diagnostic prediction in real time, which does not require specialized hardware or installation of software. This system proves that AI-driven healthcare solutions can be easily deployed and scalable by implementing both a simple UI at the front-end with a lightweight Flask back-end and a Convolutional Neural Network (CNN) based off Tensorflow.Through extensive testing and feedback, this assistive tool has demonstrated its practical viability. The real-time audio feedback, minimal interface complexity, and offline capabilities ensure that the app is not only functional but also user-centric. Compared to existing assistive applications, the solution stands out for its responsiveness and adaptability in low-connectivity environment a critical requirement for under-resourced communities.

Dermocare aims to fill that gap between self-assessing skin issues and the need for a dermatological specialist. Dermocare provides a simple tool for users to assess and learn about their skin health, to help them make informed decisions about seeking further medical assistance, as dermatological services can be limited or accessibility challenging in rural and underserved areas. The mean prediction accuracy was found to be around 85% across 22 classes of disease, which also matches up with predictions made by other deep learning models related to dermatology applications [11], [12].

Looking ahead, if further developed Dermocare could be an additional value add in the digital health sector, especially in countries where visiting a specialist is not accessible to each citizen.

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