AI-Based Tool for Preliminary Diagnosis of Dermatological Manifestations

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Abstract— Many people around the world suffer from one of the most common diseases, skin diseases, due to the lack of dermatologists and limited access to care in rural communities impacting access to timely diagnosis of their condition. Early detection is essential for avoiding complications, but conventional diagnostic techniques frequently call for expensive equipment and in-person consultations. In order to help with the initial diagnosis of skin conditions, this paper presents an easy-to-use AI-based system. The suggested tool combines a GPT-powered chatbot that provides an easy-to-understand explanation of the expected outcomes, potential causes, symptoms, and available treatments with a ResNet-50 convolutional neural network for image-based disease classification. The system seeks to assist patients and healthcare professionals in raising awareness and promoting early medical intervention by providing immediate feedback and unambiguous guidance. Because the solution is portable, affordable, and flexible, it can be used in clinical, educational, and rural settings where access to professional advice may be limited.

Keywords—Skin Disease Diagnosis, Deep Learning, ResNet-50, Medical Chatbot, Dermatology, AI in Healthcare

I. Introduction

Skin diseases are one of the most common causes of health problems that don't kill people. They affect millions of people and are often a sign of other diseases that are more serious, like Neglected Tropical Diseases. In places with few resources, doctors have a hard time making quick diagnoses because there aren't enough dermatologists, the medical infrastructure isn't good, and there aren't enough diagnostic tools.

Patients frequently encounter treatment delays, erroneous diagnoses, or superfluous visits to urban hospitals, adversely impacting their health and quality of life. Telemedicine platforms and specialized imaging systems are some of the current options in dermatology that can help, but they usually require expensive equipment or expert supervision. This makes it difficult to access and utilize these systems. The systems also often do not have user-friendly instructions or clear, patient-friendly language making it difficult for non-experts to really understand the test results and what to do next.

Filling these gaps, this proposal describes an AI-based diagnostic system that combines deep learning models (ResNet-50) for automating the classification of skin disease with a conversational AI element (GPT-based chatbot) that can give personalized language.

The user can upload images of their skin, receive accurate preliminary diagnoses, and digest useful information about the causes, symptoms, treatment options and what can be done to prevent disease in the first place. The solution proposes image-based classification and interactive guidance, creating a lightweight, scalable, and easy to use solution for receiving dermatological care. The proposed model empowers patients, reduces burden to the primary care provider, and increases awareness in underserved communities. Coupling deep learning and natural language processing can facilitate accurate predictions as well as provide useful and usable information. This will help to bridge the gap between receiving professional medical advice and engaging in your own self-assessment.

Literature Review

A. Classification of Skin Diseases through AI

Numerous studies have demonstrated that deep learning models can differentiate skin diseases using clinical images. For instance, Choy et al., conducted a systematic review of 64 deep learning models and found that these approaches were very precise when classifying typical skin conditions like acne, psoriasis, eczema and rosacea [1]. The studies mostly used macroscopic images, with the remaining review papers using dermoscopic images and reporting statistically significant performance measures based on these two categories. Liu et al. developed a skin disease classification model based on a multi-scale channel attention mechanism. The proposed model improved the pyramid segmentation attention module with an inverted residual structure in learning features from data sets, such as ISIC2019 and HAM10000 [4].

B. Generative AI in Medical Diagnostics

Several studies have explored the introduction of generative.
AI models like GPT-4 into medical diagnosis. A meta-analysis of 83 studies found generative AI models to be comparable in diagnostic accuracy to non-expert physicians but not as effective as expert physicians. This indicates that generative AI could be a useful adjunct in clinical practice [11].
Furthermore, GPT-4 has demonstrated the ability to make differential diagnoses and provide medical information. A study assessing GPT-4's effectiveness with medical tasks found that the model improved accuracy in generating differential diagnoses and medical information, suggesting potential usefulness in supporting health professionals [12].

II. EXISTING METHODS

Multiple methods for skin disease detection and preliminary diagnosis have been developed utilizing AI and digital technologies. These methods can expand dermatology practice with some degree of automation, and while valuable, each approach has limitations that could impact potential for acces- sibility, scalability, and user interactions. This section summa- rizes the major classes of existing methods and examines how they would fulfill a proposed system.

A. *Traditional Dermatology Diagnostic Tools*

Standard methodologies include clinical assessment by der- matologists, dermoscopy imaging, and laboratory tests. These provide accurate and trustworthy diagnoses; however, they require considerable resources in terms of personnel and equipment. Resource-limited settings may have a low availability of dermatologists, leading to a significant delay in diagnosis and treatment for patients. In addition, standard tools do not offer automated explanations or education for patients that can augment education and awareness for prevention.

B. *Teledermatology Platforms*

Patients can utilize teledermatology platforms to submit images remotely for evaluation by an expert. Services like DermOnline and SkinVision offer initial assessments with image upload and consultation with a dermatologist. Although useful in improving access, these services are limited by the quality of images submitted, availability of internet access, and access to an expert dermatological opinion. Additionally, they lack dynamic feedback to engage patients and provide

stepwise explanations of diseases, symptoms, and prevention measures.

C. *AI-Based Image Classification Models*

A number of AI models have been established to convert on-dermatological images of skin conditions to classification. Deep Convolutional Neural Networks (CNNs), especially ResNet model variants, have been shown to yield high diag- nostic accuracy on pitfalls such as acne, eczema, psoriasis, and melanoma. These models can accurately predict the class of a skin condition, but, their clinical utility is limited as they do not produce interpretive or user-friendly explantation, which could support patient self-assessment.

D. *Medical Chatbots and Conversational Assistants*

Medical chatbots present valuable health information and advice through natural language processing. Applications such as Ada Health and Babylon AI function as conversational interfaces that enable users to check and track ailments and symptoms in a chatbot. Contrarily, the majority of medical chatbots available today do not incorporate image-based dis- ease classification and tend to provide generic advice, rather than an individual explanation for the diagnosis.

Limitations of Existing Approaches

The methods above provide partial solutions, but there are clear limitations:

- Accessible in remote or resource-poor environments
- Not automated classification with patient-friendly explanations
- Dependent on the availability of an expert or quality of input images
- Limited support for prevention and structured learning about dermatological conditions.

First, the proposed system can provide access and address the above limitations by integrating an image classification module based on ResNet-50 with a chatbot based on GPT that provides accurate preliminary diagnosis but also provides context-sensitive structured guidance for patients and health-care team members.

III. PROPOSED METHODOLOGY

The AI-based dermatology diagnostic system proposal combines a diagnostic image classification model and conversational interface to support efficient and reliable preliminary diagnosis. The process is made of four principal components:

A. *Image Acquisition and Preprocessing*

Users take a picture of a skin lesion, or upload an image, via a mobile or web-based interface. User images are then pre-processed (the same way) to prepare it for the input to a neural network to standardize the input. The characteristics of the skin lesion image are preprocessed through: resizing the images to 224 * 224 pixels; normalizing the values of each 224 * 224 pixel; data augmentation strategies (e.g. rotation, flipping images, contrast change). This procedure of preprocessing to address the standardization of images facilitates a comparable extraction of features for a more uniform outcome, as well as helps in being able to counter different lighting, skin tones and/or image quality discrepancies.

B. *Skin Disease Classification (ResNet-50)*

The foundational model utilized in this investigation is the ResNet-50 convolutional neural network, which determines the class of a skin condition predicted from an input image. ResNet-50 addresses concerns relating to vanishing gradients through the use of residual connections which assist in identifying features such as color patterns, textures, lesions and rashes, in the image. The model will be trained using CrossEntropy loss function, and Stochastic Gradient Descent (SGD) combined with momentum and batch size of 32 throughout the training in order to ensure the model effectively and efficiently learns. The model predicts a list of probabilities of the residual classes in order to make output predictions of the class with the highest probability.

C. *Chatbot-based Diagnostic Guidance (GPT-4o-mini)*

The chatbot component understands the predicted class and generates patient-friendly structured responses. The chatbot component will provide structured components, which include the following:

- Definition and background of the skin condition

- Causes and risk factors

- Key symptoms and salient features
- Management and treatment
- Prevention and lifestyle advice

Prompt engineering produces patient-friendly, clear, succinct, and medically accurate responses while remaining transforming in facilitating patient guidance. The chatbot can also respond to any following inquiry questions, allowing individualized and personalized guidance and education of the patient.

D. *Scalability, Accessibility, and Real-Time Updates*

The technology presents a modular backend structure intended to deliver lightweight scalability and real-time updates across devices. The web-based frontend is available on mobile or desktop, minimizing upfront investment enabling users to interact with the technology. The modular structure will allow the incorporation of additional datasets, AI models, or third-party telemedicine systems in the future, affording the technology the capability to evolve in time and have greater capacity for accessibility.

E. *Workflow Description*

The integrated workflow process is as follows:

1) The image of the skin is uploaded through the interface.

2) The image undergoes preprocessing for classification purposes.

3) Based on the image, ResNet-50 will provide predictions on the most likely skin conditions present in the image.

4) The GPT-powered chat box will create a well-structured table of contents (TOC) that elaborates any preventative recommendations presented by the GPT-3 AI.

5) The final output is shown to the user and will consist of evaluation metrics alongside educational materials for the user to read.

This workflow represents an integration of image-based classification technology and conversational AI to develop a complete and user-centered diagnostic tool, for either use as a single entity or as a part of the care ecology in clinical practice.

IV. Objectives

The principal objective of the present research is to design and implement an AI-based skin disease diagnosis system that not only offers accurate assessment for a skin disease diagnosis but offers a treatment plan subsequently for patients to use. The system is intended to provide an avenue for improved access to dermatological care, particularly in settings with limited access while increasing patient trust and the continuity of preventative care.. By combining deep learning responsiveness to images with an AI generative pre-trained transformer (GPT; e.g., ChatGPT)-based conversational assistant, our system will provide reliable, rapid, and interpretable diagnostic support.

The specific aims are summarized below:

A. *Accurate Classification of Skin Diseases*

Develop and refine a ResNet-50 convolutional neural network (CNN) to automatically classify common skin care conditions, including acne, eczema, psoriasis, and rash, from clinical images.

B. *Interactive Diagnostic Guidance*

Develop a chatbot using GPT that interprets the predicted disease and produces structured explanations which include:

- Overview and definition of disease,
- Causes and risk factors,
- Key symptoms and warning signs,
- Treatment options to consider,
- Prevention and/or lifestyle recommendations.

C. *Reliable Image Preprocessing and Standardization*

Implement preprocessing steps, including resizing, normalization, and data augmentation methods, to ensure that there is consistency in the input that goes into the convolutional neural network (CNN). This helps ensure that the model has improved feature extraction as well as robustness against changes in lighting, skin tone, and image quality.

D. *User-Friendliness and User Experience*

Provide a mobile-responsive and user-friendly web interface for submitting images to receive results and interactive helpful prompts. The system aims for usability and simplicity across varying devices.

E. *Scalability and Integration with Other Systems*

Design a modular back-end architecture that can accommodate concurrent users and make changes in real time. The system should allow for future, additional integration with telehealth services and additional AI models.

F. *Awareness and Preventive Healthcare*

Combining educational and preventive information with return results to support patient understanding and proactive engagement in care; **Performance Measure:** Description of user engagement and understanding of preventive recommendations to support mechanisms to engage in care action once insights are published. The system aligns with these objectives to act as an integrated, patient-centered diagnostic tool that marries automated disease detection and interactive guidance behavioral principles to expand accessibility, awareness, and preventive healthcare in dermatology.

V. SYSTEM STRUCTURE AND IMPLEMENTATION

The suggested structure will be an artificial intelligence dermatology diagnostic platform that permits users to upload skin images, receive automated preliminary diagnosis, and receive organic structure conversation-based direction. The structure will consist of a client/server architecture that is multiplayer, consisting of a Flask backend server, MySQL database, to run the front end dashboards for users and administrators, built with HTML/CSS/JavaScript. In addition, the structure will consist of, Resnet-50 CNN to classify images, and GPT- 4o-mini to obtain conversation-based direction.

A. *Structure Overview*

The system was comprised of the following:

- **Frontend:** Developed with HTML, CSS, and JavaScript, allowing for a responsive and interactive user interface for image uploads, predictions, and chatbot responses to be displayed.
- **Backend:** This Flask is the API responsible for handling user APIs, model inference, connecting to the MySQL database, and user authentication and managing the struc- ture.
- **Database:** The MySQL database secures, stores, and manages user profiles, uploaded images for analysis, prediction results, and organized responses to chatbots, allowing two versions.
- **Model Integration:**
- **Skin Disease Classification:** A ResNet-50 CNN model extracts features from the image to use that information to predict one of the disease classes.
- **Chatbot Guidance:** The GPT-4o-mini model generates structured and stepwise responses with the predicted disease.

B. *Data Flow*

The flow of data for the system is as follows:

1) A skin lesion image is uploaded by the user through the frontend.
2) The Flask backend preprocesses the image (resize, normalize) and sends it to the ResNet-50 model for classification.
3) The predicted disease class is concatenated with the user query and sent to the GPT-4o-mini API.
4) Based on the predicted disease class, the GPT-4o-mini API generates a response to the end user that is struc- tured into causes, symptoms, treatment, and preventive measures.
5) The results of steps 3 and 4 are returned from the GPT-4o-mini API as JSON and displayed on the frontend dashboard in real time.

C. *Algorithm Workflow*

1) **Skin Disease Classification – ResNet-50 CNN:**
   a) **Preprocessing:** Input images are resized to 224 × 224 and normalized.
   b) **Feature Extraction:** The layers of ResNet-50 ex- tract visual features: edges, textures, lesions, and color variations utilizing residual blocks.
   c) **Classification:** The fully connected layers fol- lowed by a softmax layer predict the most probable disease class.

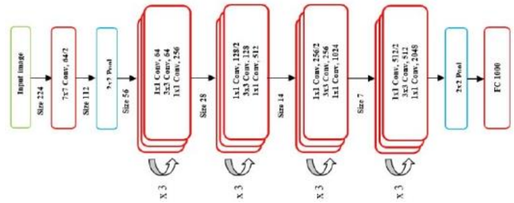

Fig. 1. Architecture of ResNet-50 showing residual blocks and layer progres- sion.

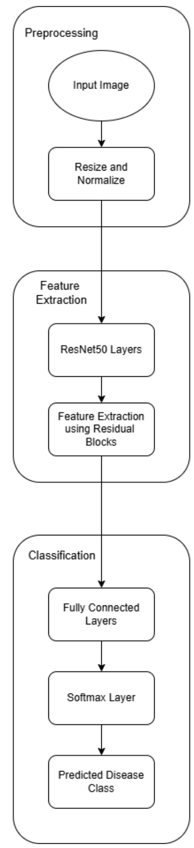

Fig. 2. Algorithm Workflow

D. *Chatbot Response Generation — GPT-4o-mini*

1) **Input Preparation:** Combining illness prediction and user question into the prompt in a structured way.
2) **Processing:** GPT-4o-mini API generates stepwise, user-friendly responses.
3) **Output:** Responses are displayed on the dashboard that provides information regarding disease definition, causes, symptoms, treatment, and prevention.

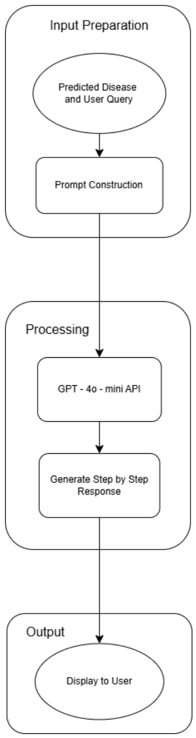

Fig. 3. Chatbot Response Generation Workflow

E. Chatbot Response Generation — GPT-4o-mini

1) **Input Preparation:** Combining illness prediction and user question into the prompt in a structured way.
2) **Processing:** GPT-4o-mini API generates stepwise, user- friendly responses.
3) **Output:** Responses are displayed on the dashboard that provides information regarding disease definition, causes, symptoms, treatment, and prevention.

F. Stepwise User Interaction

1) **User Login and Authentication:** Users provide creden- tials, and Flask authenticates access.
2) **Image Upload and Prediction:** Users upload skin images for analysis.
3) **AI Prediction:** ResNet-50 predicts the disease class.
4) **Chatbot Guidance:** GPT-4o-mini generates structured information on the disease.
5) **Result Processing:** The dashboard displays the pre- dicted disease and the chatbot response. The user can return to the chatbot and ask follow-up questions, re- upload images of different skin lesions, or ask new questions.

G. Implementation Details

- **Frontend:** HTML, CSS, and JavaScript for interactive dashboards and responsive layout.
- **Backend:** Flask for managing API python calls, user authentication, and model inference.
- **Database:** MySQL for structured storage for user data, images, predictions made, and chatbot responses.
- **Progress Logging:** All interactions with users and pre- dictions are stored for future analysis and model improve- ment.
- **Security:** Flask authentication and HTTPS encrypted access to prevent security concerns.

VI. Outcomes and Future Scope

A. Outcomes

1) **AI-driven diagnostic dashboard:** The choice of a user- friendly interactive dashboard makes the implementation of realtime diagnostic predictions of dermatology-related conditions, along with confidence indicators, simple. Al- lowing users to understand their results more efficiently and providing overall skin health awareness within their own framework. The service, unlike existing diagnostic interfaces, relies on the integration of structured chatbot dialogue with deep learning predictions to turn analytical results into actionable and understandable implications.

2) **Data-informed decision support to users:** Through the use of data from users' interactions, user submis- sions, image uploads, and chatbot threads, the platform presents a data-informed method to support users and their primary health care providers. The system dynam- ically generates user-specific recommendations that in- clude possible reasons, preventative care, and treatment pathways. In addition, the real-time analytical feedback is designed to aid decision-making and promote user engagement to diagnostic results.

3) **Competency, awareness and multilingual accessibil- ity:** The hybrid framework using the ResNet-50 model and GPT-4o-mini conversational engine supports der- matological literacy of users while being inclusive of multilinguality. The platform supports users with the chatbot and diagnostic outcomes in English, Kannada, and Hindi. This multilingual functionality increases ac- cessibility with the potential to promote broad skin health awareness and provide support to users.

4) **Open and Scalable Framework:** The platform is built on the Flask web framework for the backend and the MySQL database for data management and storage for ease of scalability, cross-compatibility, and secure data handling. The information around diagnostic results and conversations that the chatbot has

with other users are stored in a structured, encrypted format for integration into AI models or healthcare platforms in the future. The platform is modular, allows for integration into multiple institutions, and can be expanded into other regional languages and platforms.

B. Future Scope

1) Personalization via AI: Future iterations can allow risk assessment by personalizing the user experience by incorporating the user history and demographic information to improve predictions and prevention advice. Predictive analytics can recognize patterns that are suggestive of high-risk conditions that warrant intervention.
2) Clinician Dashboard: A clinician-specific view of the dermatology analytic could provide summary analytics, trends of the cases submitted by users, and alert clinicians about urgent conditions that improve clinical judgment and workflow efficiency.
3) Interoperability with Healthcare Systems: Interoperability with hospital EMR/EHR systems can provide seamless sharing of AI predictions into the medical community improving patient monitoring and follow-up.
4) Mobile App and Offline Content: Future studies can develop Android/iOS apps with offline content to include information education, AI models preloaded, and push notifications for reminders and prevention care, improving usability in resource-limited settings.
5) The implementation of Gamification will allow for adding interactive features to increase user engagement and education regarding skin health such as quizzes, knowledge checks, badges, and educational challenges, in future work.
6) Advanced Analytics and Visualization might include advanced visualization and analytics in future research such as heat maps of impacted areas and tracking of any changes, while user and clinician downloadable reports could also be conducted.
7) Security and Scalability: Security could be improved with role-based access, encrypted communication, and modular architecture for scalability and user/clinician access.

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