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Design and Evaluation of a Smartphone Application for Early Atopic Dermatitis Screening Using Large Language Model

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Abstract: ***Atopic dermatitis is form of eczema. It is a chronic disease that results from pruritus, especially when the skin is dry. People who have atopic triad have skin barrier, upper respiratory, and lower respiratory defects. Most people, especially in rural areas, lack knowledge about this chronic inflammation. The objective of this study is to create a mobile app that utilizes LLMs in Expo Go for patient assessment to ascertain the level of damage that the skin barrier undergoes due to patients' body parts. For contextually and conversationally responsive output based on users' conditions and questions, LLMs integrate into the system using Lang Chain. The mobile application raises awareness among users through symptomatic guidance, preventive tips, and educational aspects.The end product will be an application that is user friendly and efficient for both the city and rural environment.. This will enable people to access information on this skin inflammation.***

Key words: Atopic Dermatitis, Large Language Models, Mobile Health Application, AI Safety

I. INTRODUCTION

Atopic Dermatitis (AD) is an inflammatory condition of the skin that occurs in people of all ages and is accompanied by persistent itching, erythema, dryness, and irritation. This skin condition usually presents itself in the form of recurring itchy rashes, and long-term scratching might cause serious side effects, including edema, cracking, crusting, scaling, and exudation, making the patient susceptible to secondary infections. AD does not only pose physical discomfort but has been shown to affect the quality of life of the patients by affecting their sleep cycle and interfering with their daily activities [1].Recent innovations in artificial intelligence (AI) and mobile health have paved the way for intelligent dermatological systems to help in diagnosing and treating diseases. AI-based tools, such as Derm Flow, have shown promise in the field of dermatology, providing decision-making support and performance evaluations for the models used to diagnose various skin conditions. Nevertheless, most current systems specialize in classifying different skin conditions without taking into account a specific dermatological condition like AD, which is important to detect at an early stage because of its genetic and environmental determinants [2]. The fast increase in the usage of smartphones has led to the development of health applications that are promising in improving the accessibility of healthcare services. In addition to other applications like Skin Vision, Derm Assist, and First Derm, they also offer services for the preliminary assessment of images submitted by the users. Using the information about redness, dryness, and irritation of the skin, they try to make preliminary diagnoses. Yet, the efficiency of their operations is greatly determined by image quality without taking into consideration any other parameters [3]. The suggested application for early detection and preliminary assessment of Atopic Dermatitis will use artificial intelligence technology. To achieve this goal, Node.js was used to develop the app, along with the implementation of Expo Go. This framework allows for creating cross-platform applications. In this case, the diagnosis of patients is made based on both the analysis of images submitted by them and other additional data (such as degree of itching, humidity, and temperature) [4].

II. LITERATURE SURVEY

The paper entitled “Multimodal Healthcare System using LLM-based Chat-bot” [1] presents a comprehensive healthcare framework that integrates Large Language Models (LLMs) with conversational interfaces. The study demonstrates how chatbot systems enhance accessibility by enabling natural language interaction, particularly for underserved communities. The system also supports multimodal inputs, improving communication flexibility. However, it does not address critical challenges such as prompt injection attacks, hallucination risks, and misinformation generated by LLMs. Additionally, the lack of mobile deployment limits its applicability in real-world rural environments.

"Med Hub: LLM-based Healthcare System" [2] proposes a large-scale healthcare platform utilizing LLMs for patient interaction, clinical data processing, and decision support. The system effectively manages large volumes of healthcare data using cloud-based infrastructure and ensures secure communication through role-based access control. While it improves patient–doctor interaction via automated responses, it primarily focuses on backend architecture and lacks emphasis on mobile application development and multimodal data integration, particularly image-based diagnostics.The paper "RAG-Based Multimodal Behavioural Therapist for Healthcare Assistant" [3] introduces a system combining retrieval-augmented generation with LLMs to provide context-aware healthcare assistance. By leveraging external knowledge sources, the system enhances response accuracy and reliability while supporting multimodal interaction. However, it is mainly designed for behavioural health applications and lacks adaptability for dermatological disease detection.The study "Health Applications for Chronic Disease Management" [4] highlights the role of mobile health technologies in continuous patient monitoring and engagement. It enables users to track symptoms, receive medication reminders, and access healthcare information through smartphones, reducing dependency on hospital visits, especially in rural areas. Nevertheless, the system lacks advanced AI capabilities such as LLM integration and automated diagnosis, limiting its effectiveness for early disease detection."AI-driven Mobile Health Framework for Remote Monitoring" [5] presents a system integrating machine learning algorithms with mobile platforms for real-time patient monitoring. It provides personalized recommendations and early warnings based on collected data. Despite improving accessibility, the framework relies heavily on data quality, lacks explainable AI mechanisms, and does not support multimodal inputs such as image-based analysis.The paper "Conversational AI in Mobile Health Applications" [6] explores chatbot-based interfaces to enhance user interaction through natural language communication. While it improves usability and engagement, it does not incorporate advanced LLM capabilities or safety mechanisms such as prompt filtering and response validation, raising concerns about reliability.The study "Multimodal Deep Learning for Disease Detection" [7] focuses on combining medical images and clinical data to improve diagnostic accuracy. It employs explainable AI techniques to highlight critical features influencing predictions, enhancing transparency and trust. However, the model is computationally intensive and not optimized for real-time or mobile deployment."Large-Scale Dermatological Vision Model" [8] introduces a foundation model for analyzing diverse skin conditions across populations. Although it demonstrates strong generalization and high classification accuracy, it requires large datasets and significant computational resources, limiting its suitability for lightweight mobile applications. Additionally, it does not incorporate patient-specific contextual inputs.The paper "Multimodal Melanoma Detection System using Deep Learning" [9] presents a system combining dermoscopic images with clinical data to achieve high diagnostic performance. While effective in clinical settings, it lacks mobile integration, real-time feedback, and user interaction capabilities.

Finally, "Multimodal Data Integration in Healthcare Systems" [10] emphasizes the importance of combining imaging, textual, and clinical data for improved diagnosisimportance of combining imaging, textual, and clinical data for improved diagnosis and decision-making. Although it enhances personalized healthcare insights, the system primarily focuses on backend processing and lacks a user-friendly mobile interface and real-time LLM-based interaction.

III. METHODOLOGY

A. *System Overview*

The proposed system follows aclient–server architecture to enable efficient, scalable, and secure processing of multimodal healthcare data. The architecture is composed of three primary layers: the mobile frontend, the backend server, and the LLM-based multimodal AI engine. Each layer is designed to perform specific functionalities while ensuring seamless interaction across the system.

B. *Mobile User Interface Layer*

The mobile application interface is developed using React Native with Expo and serves as the primary layer for user interaction and data acquisition. It is designed to provide a simple, intuitive, and efficient user experience, enabling users to seamlessly input both visual and textual information required for analysis. The interface incorporates multiple functional components to support effective data collection and result visualization. It allows users to capture dermatological images inreal time using the device camera or upload previously stored images from the device gallery. In addition to image input, the application includes a structured patient input form that captures essential clinical details, such as the intensity of itching on a numerical scale (0–10) and the duration of the condition, specified in weeks or months. These inputs provide contextual information that enhances the accuracy of the multimodal AI analysis.

C. Backend Service Layer

The backend server is implemented using Node.js and operates as the core intermediary layer between the mobile application interface and the multimodal AI engine. It functions as a secure and efficient processing unit that manages data flow,system logic, and communication across different components of the architecture.

The backend is responsible for handling user authentication and ensuring secure access to the system. It incorporates appropriate validation and security mechanisms to protect user data and maintain system integrity.

Upon receiving input from the mobile application, the server temporarily stores the uploaded dermatological images in a secure environment to facilitate further processing. the backend performs data orchestration by combining the uploaded image with the corresponding-patientprovided information and forwarding this multimodal input to the AI engine for analysis. Once the AI module generates the prediction results, the backend processes the output and structures it into a well-organized and user-friendly format.

D. Multimodal Inference Engine

The system employs a multimodal AI engine powered by a Large Language Model (LLM) to enable intelligent and context-aware analysis of dermatological conditions. This component serves as the core decision-making unit, integrating both visual and textual data to generate accurate and reliable predictions. The pipeline begins withimage pre-processing**,** where the input skin image is cleaned, normalized, and resized to ensure consistency and reduce noise. This is followed by visual feature extraction using deep learning techniques to capture key dermatological characteristics such as texture, color variations, and lesion patterns.

In parallel, textual inputs, including itching intensity (0–10 scale) and duration of the condition, are processed and structured to provide essential contextual information. The visual features and textual data are then combined into a unified multimodal representation**,** which is provided as input to the LLM. Based on the input, the LLM performs identifying the likelihood of early-stage atopic dermatitis, estimating severity, and generating preliminary recommendations. To ensure responsible usage, the system includes a clear medical disclaimer, indicating that the results are intended for screening purposes only and not as a definitive diagnosis.

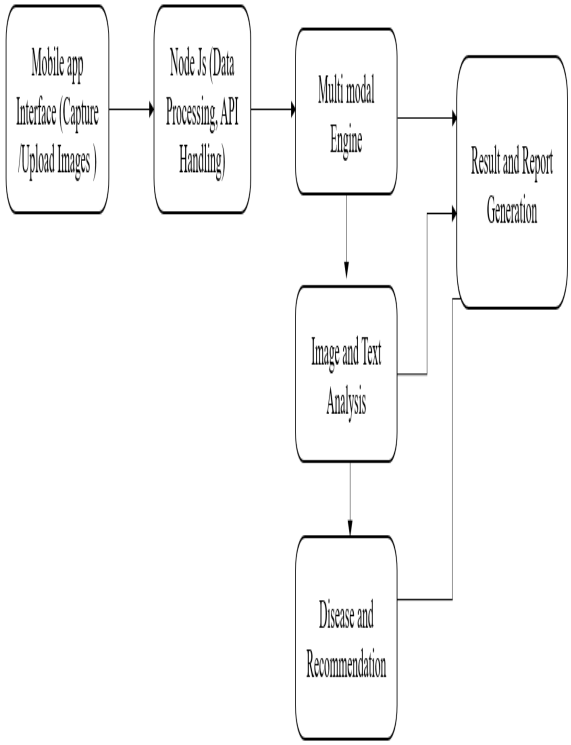

Fig 1.System Architecture

IV. APPLICATION INTERFACE AND WORKFLOW

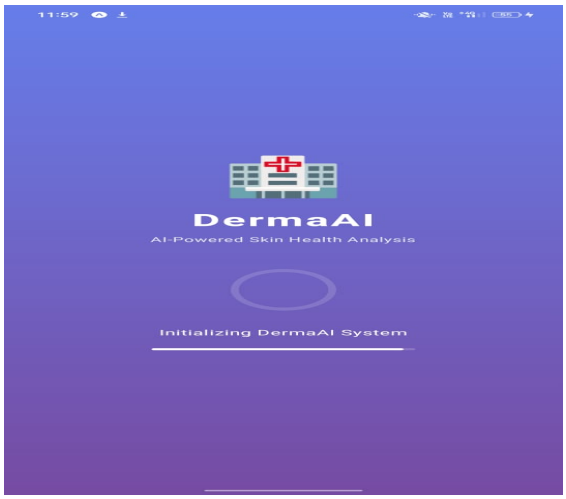

Fig 2.Application Initialization Screen

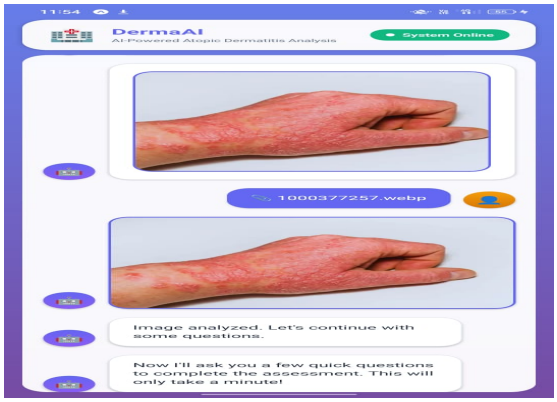

Fig 3.Image Upload and Initial Analysis

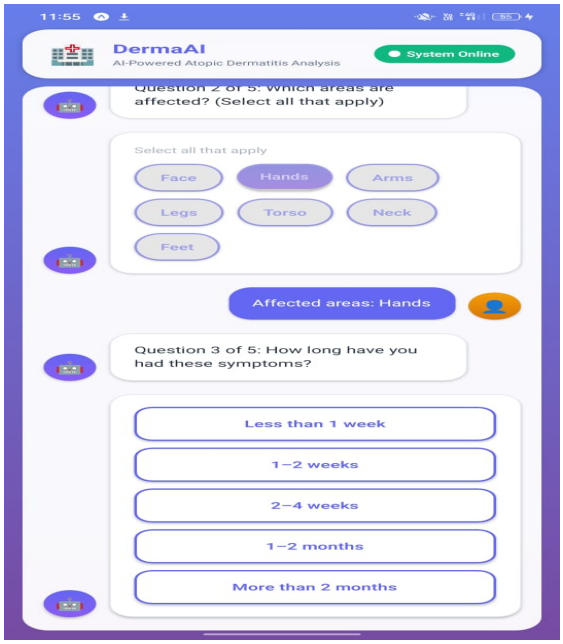

Fig 4.Patient Input and Questions Module

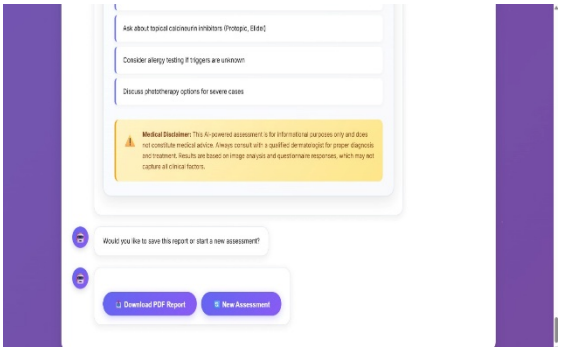

Fig 4. Result Display and Report Generation Interface

V. RESULTS AND DISCUSSION

The application was tested using sample skin images along with user inputs such as itching intensity and duration. The results indicate that the system is capable of generating meaningful diagnostic insights, including identification of early-stage atopic dermatitis, estimation of severity levels, and provision of preliminary treatment recommendations. The integration of textual inputs with visual features significantly improves the contextual understanding of the condition compared to image-only analysis.This application interface was observed to be user-friendly and responsive, enabling smooth image upload, questionnaire completion, and result visualization. The backend server ensured reliable data handling and seamless communication with the AI engine, maintaining system efficiency and stability. The system also ensures secure data transmission and provides a user friendly interface for interaction and report generation .The implementation

VI. CONCLUSION

The system also ensures secure data transmission and provides a user-friendly interface for seamless interaction and report generation.The implementation shows that the system support early stage screening , severity estimation , and recommendation generation.

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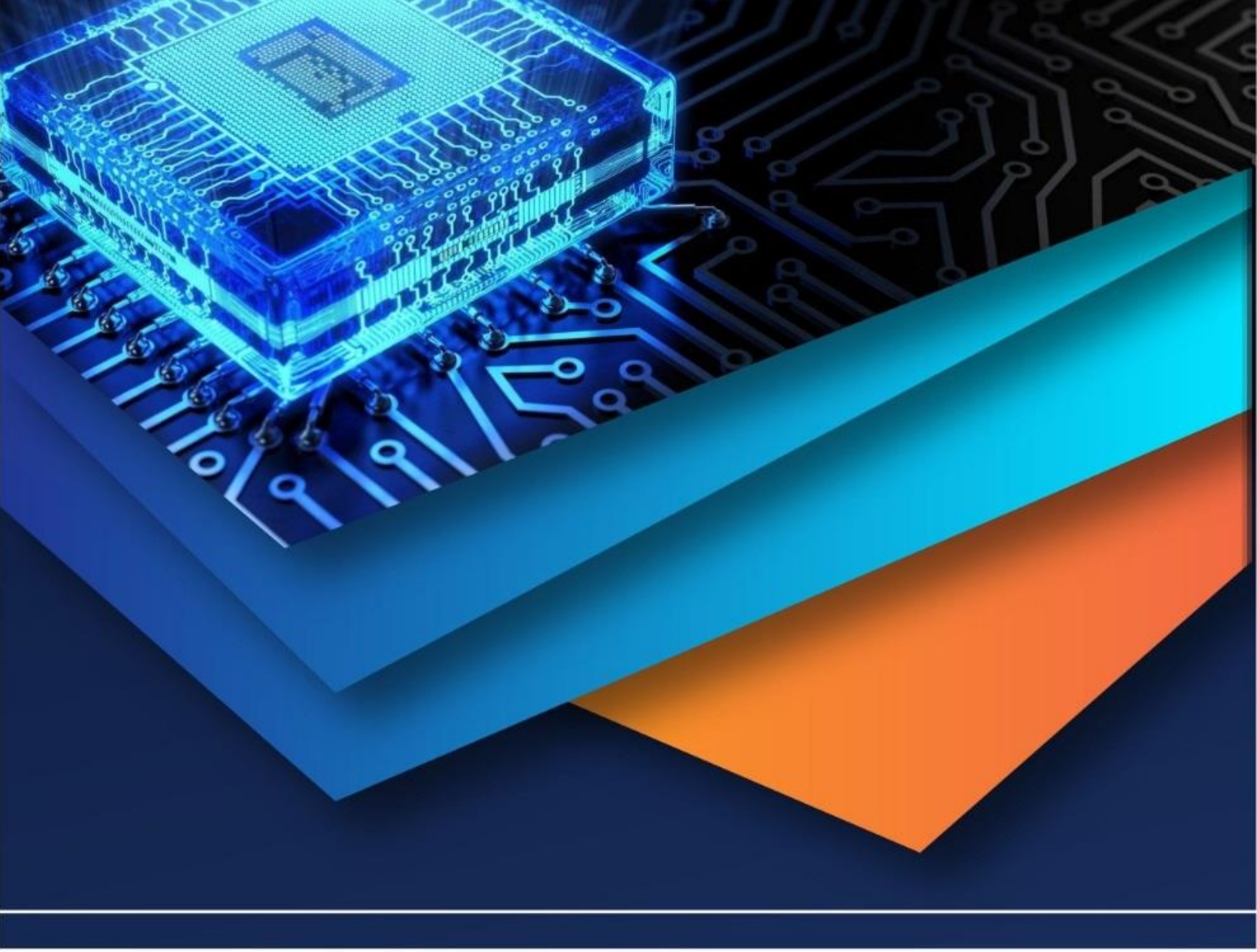

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