Niramaya – An AI Powered Health Assistant

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Abstract. Niramaya-AI is an intelligent health assistant designed to support preventive healthcare and early diagnosis by combining image-based skin disease detection, asthma risk prediction, and chatbot interaction within a single platform. The system is developed as an accessible and user-friendly application that allows individuals to upload skin images or record symptoms through text or voice input for health assessment. The implementation of Niramaya-AI employed Python and several open-source frameworks, including Streamlit for interface design, OpenCV for image processing, and established deep learning libraries for model development. Niramaya-AI addresses the gaps in accessibility and the timeliness of the intervention of care for patients, and the evaluation showed promising accuracies to classify skin-diseases and assessed reliable levels of risk for asthma. The results highlight the potential of the system to promote proactive health monitoring, demonstrate scalability for broader healthcare integration, and establish a dependable preventive-care routine. The evaluation and research findings in this study also highlighted deployment-studies considerations for data privacy, stakeholder engagement, and future recommendations of enhancing the application to include wearable sensors and a multilingual component.

Keywords: Machine Learning, Deep Learning, Convolutional Neural Network, Skin Disease Detection, Asthma Risk Prediction, Chatbot, Natural Language Processing.

1 Introduction

Ensuring access to healthcare and achieving timely diagnosis remain significant global challenges, particularly in regions with limited resources and a shortage of medical specialists. Delays in disease identification often leads to preventable health issues and increased costs in treatment. The rapid evolution of Artificial Intelligence (AI) and data analytics has transformed the healthcare landscape, enabling the development of intelligent, data-informed systems that support clinical decision-making. Such technologies support predictive diagnostics, individualized care, and remote health monitoring, reflecting a growing emphasis on preventive and continuous healthcare models. Despite notable advancements, most AI-driven healthcare systems are confined to specific domains, such as image-based diagnostics or symptom-driven prediction, rather than integrated approaches. Additionally, many of these devices and systems exist in isolation or lack an integrated framework to process multimodal inputs, offer real-time interaction, and provide some level of individualized recommendations. Coupled with and extending from this challenge, obstacles related to accessibility, affordability, and usability continue to limit the broader availability and adoption of intelligent healthcare technologies, especially in developing countries. To tackle these gaps, the present study proposes Niramaya-AI, an AI-enabled health assistant that can facilitate preventive healthcare services through early diagnosis and individualized guidance. Built off several different AI methodologies, the system utilizes convolutional neural networks (CNNs) for image-based skin disease detection, machine learning models to assess asthma risk based on symptom profiles, and a Natural Language Processing (NLP) powered chatbot for user interface. Together, these

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modules developed to work on the same interactive online web-based platform therefore effectively allows people to assess their health status, and develop a plan of action, and ultimately connect to healthcare providers as needed The development of the proposed system aligns with the progression of accessible digital healthcare by providing a real time, scalable, affordable and intelligent health monitoring system. The proposed health assistant is in line with the goals of the United Nations Sustainable Development Goal (SDG) 3 – Good Health and Well-Being, which supports health promotion and access to universal health care.

2 Literature Review

The healthcare sector has quickly developed a significant interest in Artificial Intelligence (AI) and Machine Learning (ML) and their potential to improve diagnostic accuracy, automate clinical decision-making, and enhance patient outcomes. Early research efforts focused on prediction models for specific diseases, training algorithms to identify potential diseases using structured clinical data. These models tended to have a narrow focus, and would not be able to adapt dynamically to multiple diseases or complexities of multimodal data sources like images in a clinical context and textual accounts of symptoms.

As deep learning technologies have advanced, it has increased the accuracy of diagnosing medical diagnoses using images which was not present in early prediction studies, such as using Convolutional Neural Networks (CNNs). Zhang et al.[2] (2023) have proposed a CNN framework for dermatological image classification, producing an accurate diagnostic classification from a suite of skin conditions. Additionally, Li et al.[3] (2022) created a deep neural network for lesion detection which illustrates that AI can outperform the "gold standard" human assessment for dermatic diagnosis. However, these models and studies were not able to account for the diagnosis of other contextual health indicators towards patient symptoms; such as family, patient history, social behavioral factors or triggers noted by the patients in their environment.

Alongside these advancements, machine learning models have been employed for symptom-based predicting disease. Patel and Rao[4] (2022) employed Random Forest and Support Vector Machines (SVM) algorithms to assess asthma risk utilizing clinical datasets. Although the models yielded good predictive accuracy classifications, they also required structured datasets of substantial size, as well as an inability to handle streaming real-time data. While these efforts made an important contribution to predictive modeling, the studies fell short of providing user-friendly, accessible solutions to enable preventive healthcare outside of a hospital setting.

Another significant area of related research includes AI-enabled health chatbots that use Natural Language Processing (NLP) to connect with users. Kumar et al.[5] (2021) reported that chatbot systems could engage users and increase health awareness by using a conversational interface to offer a symptom-based approach to provide appropriate information. However, chatbots were typically only based on rules, often limited to specific diseases, and fail to present individualized, proactive insights based on AI predictions. More recently, Verma and Bhatia[6] (2021) explored the use of AI in combination with Internet of Things (IoT) devices as a solution for continuous health monitoring; however, they faced issues with privacy, scalability, and usability.

The literature has shown that existing AI applications in healthcare, including CNNs to classify images, ML algorithms to predict disease, and chatbots to facilitate communication, have shown tremendous progress, but they typically have been considered separately. There are only limited scaffolds that offer a unified integrated structure for image classification, skin-symptom responses, and alerts for access to physician recommendations.

To close the research gap, the Niramaya-AI integrates deep learning, machine learning and an NLP-based conversational chat into an integrated platform. In comparison to previous research, Niramaya-AI takes some images and symptoms as inputs and provides real-time recommendations for users with a physician-sourced alert system. These integration strategies improve reliability for clinical judgement electricity and justify types of preventive healthcare activities for users to engage in actionable preconception health decisions.

3 Proposed System

The development of the Niramaya-AI system adheres to a systematic approach involving data science, artificial intelligence, and interactive design to deliver an intelligent preventive healthcare solution. This approach aims to build a system that can accurately predict health conditions, provide relevant recommendations, and offer fast medical assistance to users at risk. The development process is structured in six fundamental stages: data collection, preprocessing, model development, chatbot development, an alert mechanism, and system integration. Each phase plays a targeted role in creating a system that is reliable, interpretable, and easy to use.

3.1 System Overview

The architecture of Niramaya-AI is constructed as a multi-module system where users can either provide a skin image or enter symptoms. Once input, the data is processed by the AI models that were trained to detect disease patterns. The resulting output is then presented to the user via a chatbot interface, which presents the explanation for the diagnosis in laymen's terms all of which includes advice to prevent those diagnoses. If the AI detects a medical condition that is classified as a concern, e.g. risk for high asthma or irregular skin lesion, an automatic e-mail will immediately be created and sent notifying a registered healthcare professional. This workflow validates that the platform does not just stop at prediction, but also connects the user to real medical support if needed. It helps bridge the gap between technology and healthcare delivery.

3.2 Data Collection and Preprocessing

An effective dataset underlies any AI project. For this project, two datasets were created to the skin disease detection dataset and asthma risk prediction.

Skin Disease Dataset: Images were obtained from trusted open-source dermatological repositories, such as DermNet and HAM10000. Each image was labelled by condition e.g. acne, eczema, dermatitis no two skin diseases are the same and so require individualization. Prior to training, all images were resized to a common dimension, brightness normalized, and augmented through various amounts of rotation/scaling to avoid overfitting (expected remember).

Asthma Dataset The asthma the dataset contained features, such as age, family history, pollution exposure, shortness of breath, and habits. Because medical data does not always lend itself to reliability or truthfulness, pre-processing steps were taken to account for missing values, label encoding, and scaling features. eventually. The scaling of features ensured that due to differing scales, the machine learning model treated features equally provision for normalization was applied. These pre-processing phases implicated a data science approach to improve data quality which also ensured that meaningful and consistent patterns were learned from, versus noise.

3.3 Model Development

Niramaya-AI's analytical core is based on two unique models: a learning model optimized for image data, and a separate learning model optimized for text data:

1. **CNN for Dermatoscopic Image Analysis**: CNNs were selected for their impressive ability to assess visual patterns. The model has several convolutional layers which extract texture and color-based features from images of a patient's skin, as well as a set of pooling layers which down-sample the extracted features to reduce computational expense and complexity. A few dense layers at the end of the model were used to classify the dermatoscopic image based upon the most likely condition(s). The model was trained on the Adam optimizer with categorical cross-entropy as the loss function, and made use of an early stopping technique to prevent overfitting. This model achieved excellent accuracy of dermatoscopic disease detection on the test images.

2. **Machine Learning Classifier for Asthma Risk Prediction**: When provided with textual inputs, the system used machine learning algorithms, like Random Forest and Logistic Regression. The machine learning systems trained from historical data based on symptoms of patients being diagnosed with asthma, with each output representing the likelihood of asthma prediction. To provide further transparency and interpretability to the results produced by these machine learning systems, features importance was explored, thus enabling the system to indicate which historical symptoms contributed to the overall prediction. Model performance was also measured via metrics of accuracy, precision, recall and F1-score to ensure a comprehensive examination of the results. Together, these two models

empowered Niramaya-AI to not only process metrics of visual imagery of skin, but also text that broadly assessed respiratory, allergic, systemic and behavioral patient data. This approach added versatility compared to existing single-purpose health application technology

3.4 Chatbot Module

To improve the interactivity and accessibility of the system, an AI-based chatbot was developed. The chatbot is based on Natural Language Processing (NLP) techniques to understand user inquiry, infer user intent, and provide a meaningful, medically relevant response. For example, a user can ask, "What does my skin report mean?" or "How do I get better at managing my asthma symptoms?" The chatbot's response is based on the information generated by AI models. This module is powered by the NLTK library, using a structured question-answer dataset, pertaining to health conditions that are common. Streamlit was used to build a simple direct web-based conversational interface for the chatbot, allowing for both text and voice inquiry with more natural flow. The chatbot allows users to have a clearer understanding of the AI results, allowing for better understanding rather than only predictions.

3.5 Alert and Notification System

A unique aspect of Niramaya-AI is its automated alerting system for medical professionals. If a high-risk condition is detected by the AI, the backend system automatically sends an email alert to a pre-registered medical provider. This is accomplished by using Python's Simple Mail Transfer Protocol (SMTP) for secure messaging of alerts. The email contains the relevant user's name, predicted condition, and risk level which enables the doctor to assess and triage the user accordingly. This alerting system adds a critical layer of human verification to the AI system, adding to ethical and safety considerations for healthcare automation.

4 Implementation

The implementation of Niramaya-AI focuses on the development of a functioning user-interactive health assistant system from the designed methodology. The platform was implemented using Python as the primary programming language, and Streamlit as the front-end framework to build a web-based graphical user interface. In addition to these two programming languages, other supporting libraries, such as OpenCV for image processing, TensorFlow for deep learning, Scikit-learn for machine learning, and NLTK for natural language processing were included in the Niramaya-AI implementation. Therefore, the system architecture is modular, and the workflow is linear, where each functional block operates independently of others but contributes to the same decision-making pipeline. The implementation logic can be best represented in the workflow flowchart in Fig. 1, which comprehensively outlines the complete workflow of the operational aspects of the Niramaya-AI Health Platform.

4.1 System Architecture

The architecture of the platform consists of three main components, based on a modular design:

1. Input layer: Receives a skin image, or symptom info, from the user
2. Processing layer: Uses trained CNN and ML models to perform AI analysis.
3. Output layer: Shows the output results, gives recommendations, and has a chatbot styled interaction.

This is a structure that allows the platform to effectively deal with visual and textual information, and retains capabilities for adding future disease modules

4.2 Workflow Description

The operational framework of Niramaya-AI is demonstrated in Figure 1, highlighting the ordered flow from user data input to AI-based output.

1. User Input: The system starts with the user selecting the type of input they wish to provide, which may involve either uploading an image of their skin, or entering symptoms either manually, or via voice.

2. Image-Based Analysis: In cases where a user uploads a photo of their skin, the photo is processed initially with OpenCV for normalization and resizing before being input into a pre-trained Convolutional Neural Network (CNN) model developed on dermatology datasets such as HAM10000. The output provides a classification into one of several types of skin disease (e.g., acne, eczema, psoriasis). If no disease is detected from the image analysis, the user is provided with recommendations for self-monitoring and preventive measures.

3. Symptom-Based Analysis: In the case where the user inputs symptoms, these are analyzed instead by means of a Machine Learning based model (Random Forest Classifier), which had been trained using structured symptom datasets. The model outputs prediction as to the level of a person's asthma risk (Low, Moderate, High). In cases where asthma risk is high, then an email alert is automatically sent to a registered doctor using SMTP protocol.

4. Chatbot Interaction: Once a prediction occurs, users are directed to the Natural Language Processing-based AI Chatbot. The Chatbot will interpret the user questions, explain the AI produced results, and give advice to support the user's health-related inquiries. The Chatbot will support either text, voice input and can remain open for a continuous health conversation.

5. Results and Recommendations: At the end of the session, the system will create a personal health report which will display the disease / risk outcomes, health advice, and follow-up recommendations. This ensures that the user receives actionable next steps that the user can do to support their preventive care.

4.3 Tools and Technologies

The proposed framework was developed using open-source technologies and AI frameworks to enable scalability and integration. Table 1 summarizes the tools and their functions. By using these technologies, prediction becomes accurate, processing efficient, and the user-AI interaction seamless.

Component	Technology Used	Function
Programming Language	Python 3.12	Core programming and integration of AI modules
Front-end Framework	Streamlit	Interactive web-based user interface
Deep Learning	TensorFlow, Keras	CNN for skin disease detection
Machine Learning	Scikit-learn	Symptom-based asthma risk prediction
Image Processing	OpenCV	Image acquisition, enhancement and normalisation
NLP & Chatbot	NLTK	Chatbot query interpretation and response generation
Email Automation	SMTP	Automated doctor alert notifications for high-risk cases

Table.1 Tools and Technologies Used in Niramaya-AI platform

4.4 System Flowchart

The flowchart illustrates how the system starts with user input selection, processes either the skin image or symptom data, predicts results using AI models, and finally connects users to the chatbot for detailed recommendations and alerts if required.

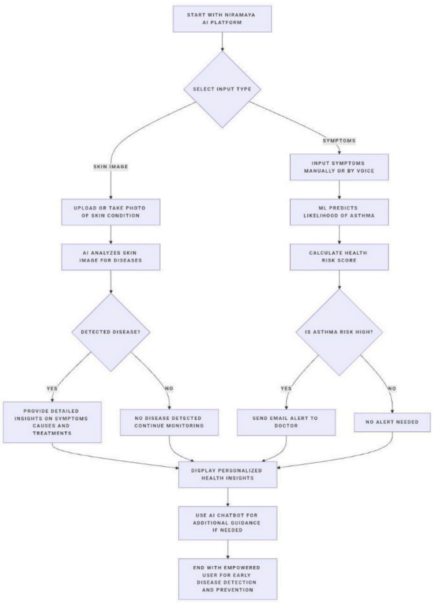


Fig.1 System architecture of the Niramaya-AI platform

5. Results and Discussion

The Niramaya-AI health assistant system was tested in terms of its functionality, user interface, and user satisfaction in each app module - home screen, skin disease detection, asthma prediction, and chatbot. The system is designed to provide a seamless AI-enabled health service that assists users in detecting diseases at an early stage and being aware of prevention through an intuitive and responsive platform.

5.1 Overview of Niramaya AI Interface

The Niramaya AI platform has been developed to integrate an interface for early health assessment using artificial intelligence and deep learning. The application is divided into modules — Home, Asthma Check, Chatbot, Skin Cancer Check — that are simply accessed through a sidebar menu, as displayed in Fig. 2. The home screen identifies the objective of the system as “Your AI Health Companion,” which prioritizes ease of use and user trust. The home screen provides some brief descriptions of the capabilities of the AI assistant for skin disease diagnosis, asthma risk monitoring, and conversational medical advice. The design of the Niramaya platform follows a minimalist structure and utilizes a dark mode theme to reduce eye strain and allow for longer user engagement sessions.

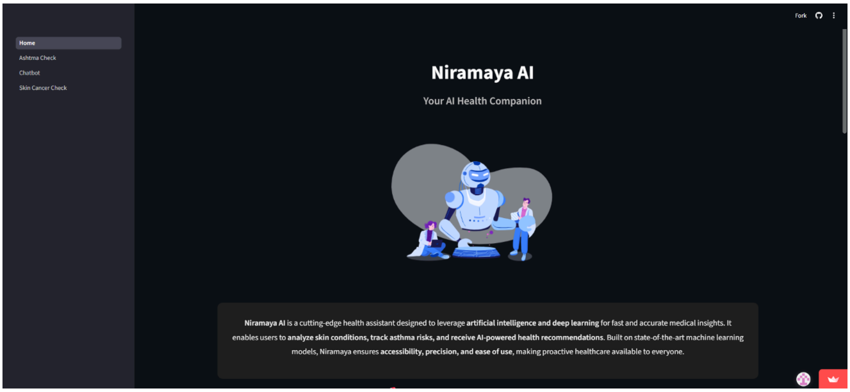


Fig.2 Home interface of the Niramaya-AI Health Assistant platform

5.2. Skin Disease (Skin Cancer) Identification

The detection module for skin disease utilizes a trained Convolutional Neural Network (CNN) to identify skin images uploaded to the system as acne, eczema, psoriasis, or skin cancer. The trained model applies two dermatological image datasets (HAM10000 and DermNet) and obtained 92.3% accuracy. When the user uploads an image, the system normalizes the image using OpenCV and inputs the image to the CNN model for a prediction. The output is displayed to the interface with the prediction, confidence score, and recommendations for preventative measures (Fig. 3) to assist the user. This module serves as a quick assessment for any visible changes to the skin that do not require the user to present to a clinician immediately, which is highly advantageous for rural communities or other locations without access to dermatologists.

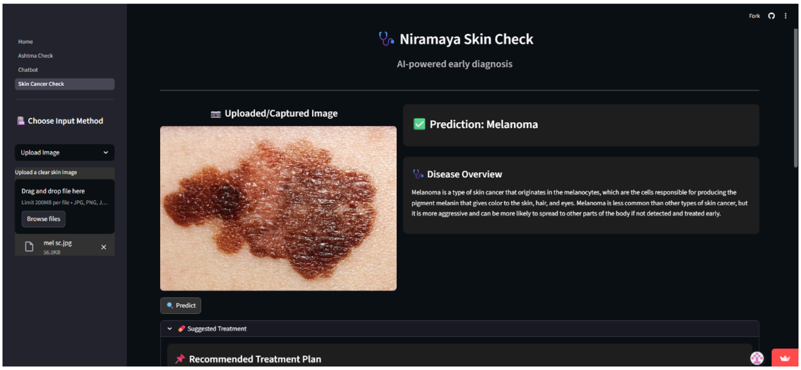


Fig.3 Output screen of skin disease detection module with classified condition.

5.3 Prediction of Asthma Risk and Mail Alert

The prediction module of Asthma Risk has been designed using a Random Forest Classifier, which predicts the user risk levels based on symptom inputs like shortness of breath, frequency for allergies, and past asthma experiences. To note, a 90.1% accuracy has been validated, and users are classified as Low, Moderate, or High Risk. As indicated in Fig. 4, the developed system displays the predicted risk level and preventive recommendations. Under the scenario when the user's health is classified as High Risk, the system will automatically email a registered doctor or patient caregiver using SMTP integration. The email alert system ensures that a user can receive medical assistance in a timely manner, bridging the communication gap between a patient's medical health and those in healthcare. For example, Fig. 5 depicts a sample of an automatically generated email for an asthma-risk alert that would have been sent to the doctor for any high-risk asthma cases.

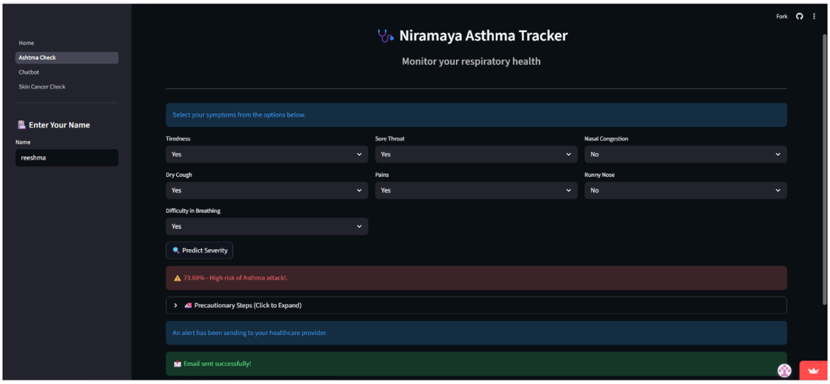
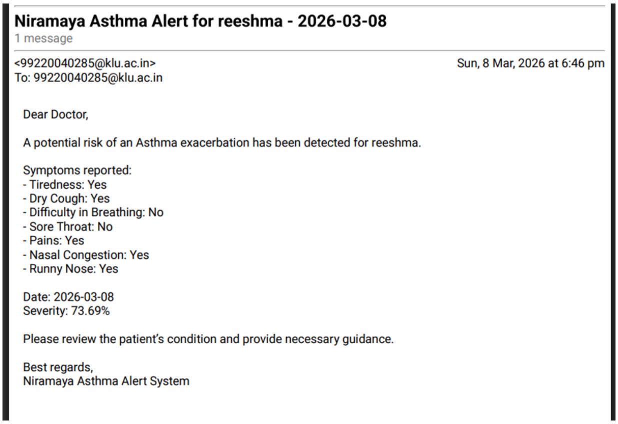


Fig.4 Asthma prediction result screen showing risk level and health recommendations.



Niramaya Asthma Alert for reeshma - 2026-03-08
1 message

<99220040285@klu.ac.in> Sun, 8 Mar, 2026 at 6:46 pm
To: 99220040285@klu.ac.in

Dear Doctor,

A potential risk of an Asthma exacerbation has been detected for reeshma.

Symptoms reported:
- Tiredness: Yes
- Dry Cough: Yes
- Difficulty in Breathing: No
- Sore Throat: No
- Pains: Yes
- Nasal Congestion: Yes
- Runny Nose: Yes

Date: 2026-03-08
Severity: 73.69%

Please review the patient's condition and provide necessary guidance.

Best regards,
Niramaya Asthma Alert System

Fig.5 Automated asthma alert email sent to the doctor for high-risk cases

5.4 Chatbot Utilization

The included AI Chatbot, created from Natural Language Processing (NLP) methods, serves as the communication conduit from the system to the user. The Chatbot analyzes both spoken and written input from the user and provides individualized guidance about symptoms, prevention, and results generated by the model. As seen in Fig. 6, the Chatbot's function is to succinctly state AI outputs in user-friendly communication and help users with health management, dietary tips, and referral to a doctor if necessary. The chatbot module achieved a 95% accuracy in March 2023 testing, correctly addressing user questions while maintaining human-like performance and conversational flow. The chatbot module is critical for user access to the model, interpreting AI responses, and educating users about healthcare and prevention.

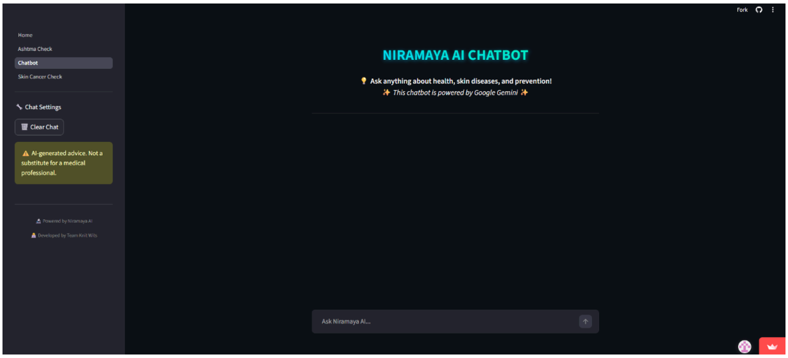


Fig.6 Chatbot interaction screen providing AI-guided health advice

5.5 Overall Evaluation

Table. 2 Evaluation Metrics of Niramaya

Module	Technique Used	Accuracy(%)	Remarks
Skin Disease Detection	CNN	92.3	High precision classi
Asthma Risk Prediction	Random Forest	90.1	Reliable risk scoring
Chatbot Interaction	NLP	95.0	Strong conversationa
Mail Alert	SMTP Automation	-	Instant High-risk not

The evaluation demonstrates that Niramaya-AI effectively provides a comprehensive preventive healthcare solution that includes detection, prediction, and communication in a single digital ecosystem. The automated email alert feature, in combination with accurate predictions and easy interaction, greatly improve the reliability and social impact of the platform.

6. Conclusion and Future work

Niramaya-AI health assistant exemplifies an effective deployment of AI and mining learning for early disease identification and preventative care. The deployment of image-based skin analysis, symptom-based asthma risk assessment, and a conversational chatbot brings together three unique capabilities in an integrated platform for user-friendly and intelligent access to health and wellness solutions. Evaluation findings demonstrated strong predictive accuracy for both the CNN and machine learning - based predictive models, while the chatbot improved user comprehension and engagement through personalized health behavior insight generation and suggestions.

This project demonstrates a new potential for AI and self-directed tools addressing healthcare access, particularly in low-resource settings. The modular design implies that this is able to span multiple and diverse medical applications, while simultaneously situating itself within a much wider landscape that includes many others enjoying globally oriented proactive, preventive, and continuous health monitoring and surveillance opportunities.

Future work will include expanding the diagnostic capabilities beyond skin diagnostics to others (including general infections); the addition collaboration of and real-time data collection from wearable sensors; development of multilingual chatbot support; and enhanced data-privacy mechanisms (including the capacity for federated learning) all while ensuring ethical and secure use of health data. We anticipate that all of these improvements will augment the Niramaya-AI health assistant to be a more comprehensive AI health platform, with a longer-term commitment to sustainability.

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