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Leveraging AI for Holistic Health: An Integrated Web Platform for Nutritional Guidance, Disease Detection, and Mental Health Support

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Abstract— This paper presents an AI-based web service aimed to encourage integrated health management involving nutritional counseling, disease screening and mental health assistance with the help of an interactive chatbot. The platform's Nutritional Guidance feature provides users with customized insights into a wide range of food items, offering detailed nutritional information and recipe preparation instructions, with ingredient quantities that adjust based on serving size. The Disease Detection module assists users in characterizing some of the most common diseases with sub- sections for heart disease, diabetes, and skin diseases, all of which are driven by pre-trained, reliable models, to provide the right information in managing chronic diseases. Moreover, the platform also includes a Large Language Model (LLM)-based chatbot, implemented as an extension of Llama 3 based on Retrieval- Augmented Generation (RAG), for providing task- specific recommendations via interaction in text and voice. For people with cardiovascular or other chronic diseases, the chatbot may recommend nutrient - targeted foods that could be searched by users who would then see nutrition, recipe information and, if desired, place an order with the service directly. Involvement of medical personnel, specialisation in cardiology, diabetes and dermatology and collaboration with a nutritionist-based information, increases the platform's ability to facilitate physical well-being and mental well-being. This work illustrates the power of AI-based systems to deliver accessible, personalized health assistance, where users have access to a single platform for management of their holistic health and wellness.

Index Terms- AI-driven platform, holistic health management, nutritional guidance, disease detection, mental health support, LLM-powered chatbot, food nutrition, recipe customization, heart disease monitoring, diabetes care, skin disease detection, chronic illness support, Llama 3, Retrieval- Augmented Generation, personalized nutrition, healthcare technology, unified health platform.

I. INTRODUCTION

Artificial intelligence (AI) integration in health management systems is changing the paradigm of personalised wellness by adopting a situation-aware, user-centric perspective. This research introduces an AI-driven web platform.

Integrate nutritional consultation, disease screening, and mental care using an interactive chatbot featuring both text and speech functions. Using Llama 3 and Retrieval Augmented Generation (RAG), the platform fills gaps in nutrition, chronic disease management, and mental health, and helps users to reach informed healthcare decisions.

The **Nutritional Guidance module** is an adaptive nutritional feedback tool that generates customized nutritional advice and recipe recommendation, which conforms to user health objectives and nutritional requirements, e.g., heart-healthy/low-glycemic food choices. An integrated ordering system facilitates adherence through automatic buy of recommended food items at one click.

Disease Detection module is directed to treat chronic diseases such as heart disease and diabetes, and skin disorders. By making use of pre-trained models, it provides those with personalized information, predictive advice and educational materials in order to foster proactive health management. One of the key capabilities is the LLM-based chatbot, further equipped with RAG, providing real-time, contextually-relevant responses in the form of text and real-time audio. This chatbot is a virtual health copilot, and by giving commands that are actionable, like low-sodium diets for hypertension. Backend based on MongoDB, the platform effectively handles user data and iteratively refines the recommendation process to provide a personalized experience. Working with healthcare providers and nutritionists guarantee yield and reality, undercutting AI-based recommendations by firmly attaching them to current medical and nutrition science. This study also demonstrates a single, unified approach for personal health management, which integrates physical, mental health, and easy access to resources. The platform shows great promise for facilitating positive use of technology to improve user well-being by providing a consistent, user- oriented digital experience.

II. LITERATURE REVIEW

We talked about how artificial intelligence (AI) in healthcare can be used for good i.e. disease monitoring, personalized nutrition and overall health support. Zhang et al. [1], Gore et al. [3] define role of AI in healthcare advancement based on physiological insights public health support. Yet, they also caracterized the absence of whole-everything platforms allowing for nutrition and chronic disease management. So, we take care of that and solve the constraints by building a single woven platform that help disease early detection, nutri-petnerhip and mental wellness for having a healthy life.

Verma et al. [2] and Ghosh [7] addressed the problem of personalized nutrition, explaining the difficulties such as intrinsically different human physiology and no personalized advice in current solutions.

Our platform closes this gap with the use of Retrieval-based Augmented Generation (RAG), powered by Llama 3 to deliver personalized nutrition suggestions. The solution makes personalized dietary advice for users, specifically people living with heart disease or diabetes, which is a far cry from general recommendations.

Kouroubali et al. [4] designed an AI-based care platform on the concept of frailty, that is to say mainly applicable for old patients. The restricted age demographic made it not suitable for the universal use in chronic disease management among diverse population. The broader our project is by introducing disease management to include different chronic diseases (eg cardiovascular disease, diabetes and skin disorders) across all age ranges so it is not only a “bigger” health solution.

Rahman et al. [5] researched the requirements of chronic disease management but stated that no integrated dietary and lifestyle credibility existed Rahman Our platform fills this gap with the integration of Nutritional Guidance Module, and diseases detection, thus enablign people to deliver adjustments in their diet in real-time.

Also, the platform has an ordering system to support the ability of users to follow dietary recommendations and ensure future health management. Coman et al. [6] & Ahmadi [8] already on the potential of remote health monitoring and universal digital health transformation but highlighted some challenges that are data scalability and restrictive of user-defined data. To overcome these, we use MongoDB for secure and scalable data storage of the user health data, diet preferences and order history in our platform. This configuration allows real time data personalization which is very helpful for responsiveness and agility of our platform.

Liu et al. [9] and Arefin [14], Review the literature on chronic disease prediction via AI, concentrating on few- shot learning and predictive models. The proposed approaches could not lead to instructions for a healthy diet in real time. Our project solves this short coming by providing live support via chatbot and suggesting personalized dietary plans as well as continuous disease management to deliver actionable health guidance to users. Yang et al. [10], & Rostami [11] explored the large language model (LLMs) option for nutritional chatbots but they offered only at a similar basic aspect regarding nutrition. Much as the chatbot was unable to promote integrations with disease features for chronic disease support. The solution is to fuse nutrition recommendations with disease-specific advices and give user a comprehensive health experience to deal with their dietary needs as well as their chronic health condition through our platform.

Yu et al. [12] and Banerjee et al. [18] here provide a review of biomedical informatics LLMs and their applicability for personalized health support.

Nevertheless, they highlighted that there is a chasm in real-time responsiveness to health management apps. This solves most of the problems, our platform solves by using LLMs + RAG for real-time personalized health insights; this way it keeps the users interested, with accurate context-sensitive interaction and timely response.

Jindal et al. [20], Ahmed et al. [21], bhatt et al. [23] Developed disease prediction models for heart disease and diabetes but they are not integrating with lifestyles. Our project builds upon these models and provides intelligent food suggestions based on users’ health profiles, promoting personalized lifestyle changes necessary for their chronic disease based needs.

III. METHODOLOGY

Nutritional Guidance Module

Users have access to individualized nutritional guidance according health needs. This section gives dietary guidance specific to the modality: recipes and ingredient substitutes for specific diseases (eg cardiovascular disease, diabetes). An integrated supply chain offer the chance to put items into an user shopping cart and buy for food adherence.

Disease Detection Module

This Module on monitoring of chronic disease (Heart Disease, Diabetes and skin conditions) It can use the strength of pre-trained models to provide detection, educational content and lifestyle advice that promotes a health literacy approach.

LLM-Powered Chatbot with RAG

Using Llama 3 with Retrieval-Augmented Generation (RAG), the chatbot offers real-time, context-aware health recommendations. Chronic condition users, e.g., diabetes, are presented with customized dietary advice and recipes in line with health requirements, which promote engagement through conversational, actionable advice.

Order Retrieval System

The order system bridges dietary guidance with practical implementation, allowing users to search for and purchase recommended items directly. This functionality promotes adherence to health-aligned foods, making dietary changes more accessible.

A. Novelty of the Project

Comprehensive Health Platform: Nutrition information, disease identification and behavioral counseling integrated with a single user-friendly platform targeting multiple

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aspects of an individual's well-being.

AI-Powered Personalization: Using a combination of a Large Language Model (LLM) with Retrieval-Augmented Generation (RAG) plume to deliver personalized remote health advice in real time, to each individual's profile.

Efficient Data Management: Utilizes MongoDB for scalable storage, enabling adaptive and personalized recommendations by tracking user preferences.

Integrated Ordering System: Links amount of recommendations to action by enabling users to easily indicate, add and get food by the platform.

Expert Collaboration: Developed in consultation with health nutrition experts to provide evidence-based and trustworthy guidance.

Holistic Approach: Diabetes with a focus on physical and psychological health, to support preventive and therapeutic lifestyle modifications.

B. Dataset Analysis and Description

This study utilizes three primary datasets to develop and evaluate the AI-driven health management platform: Skin Cancer Detection, Heart Disease Detection, and Diabetes Disease Detection datasets.

1. *Skin Cancer Detection Dataset*

Source: International Skin Imaging Collaboration (ISIC). Overview: A total of 2,357 images of skin lesions with different malignancies and benignities are included in the dataset.

Analysis: The dataset allows multi-class classification, thus the model can differentiate between various skin diseases. Major preprocessing steps are resampling and normalization so that input images could be standardized. Moreover, data is inputs in it, i.e., an augmentation and contrast adjustments are applied to enhance model generalization and robustness.

$$p(y=1|x) = 1 / (1 + \exp(-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)))$$

2. *Heart Disease Detection Dataset*

Source: https://www.kaggle.com/datasets/rishidamarla/heart-disease-prediction.

Overview: This dataset includes 76 attributes, with 14 commonly used features for predicting the presence of heart disease. The target variable is binary, indicating the presence (1) or absence (0) of heart disease.

3. *Diabetes Disease Detection Dataset*

Source: Kaggle, sourced from the National Institute of Diabetes and Digestive and Kidney Diseases.

Overview: This dataset contains data from female patients of Pima Indian heritage, aged 21 years and older. The target variable is binary, indicating diabetes presence (1) or absence (0).

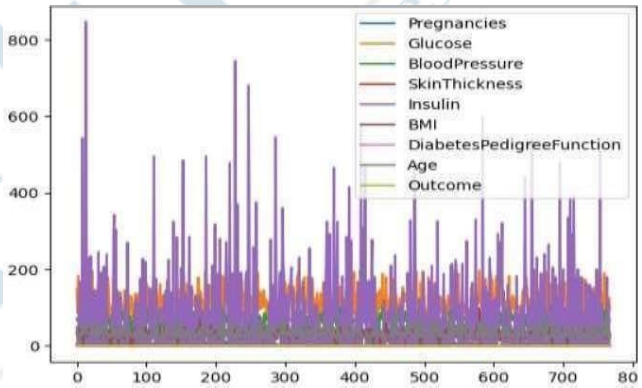


Figure 1. Diabetes Analysis

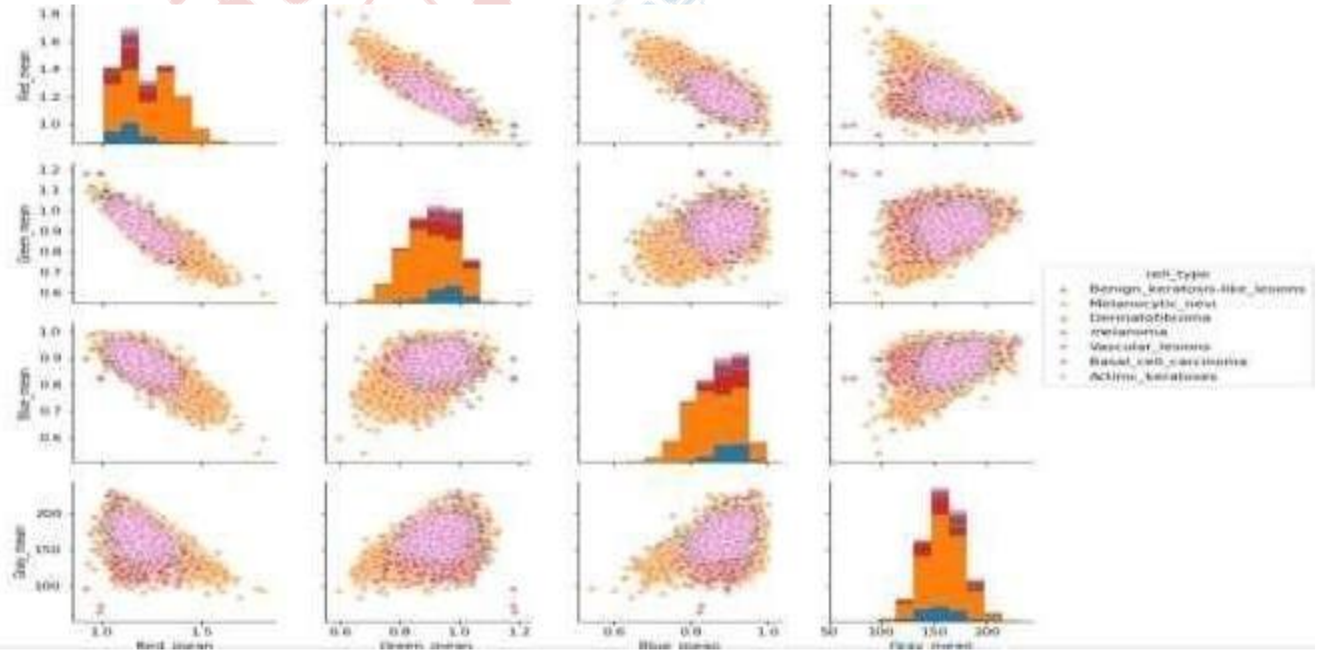


Figure 2. Distribution of different cell types over colors

C. Algorithm Justifications:

The implementation of the variety of algorithms in this work is important to properly address nutrition guidance, disease recognition, and mental health assistance. Subsequent describes the most commonly applied algorithms available in the platform and explains their selection in accordance with their appropiateness for each particular task.

1. *Convolutional Neural Networks (CNN) for Skin Cancer Detection*

Convolutional Neural Networks (CNNs) are employed for skin cancer detection due to their effectiveness in image classification tasks, specifically for distinguishing between malignant and benign skin lesions. Key justifications include:

Feature Extraction: CNNs exploit convolutional layers to select complex features and textures from the skin images, further improving classification performances of skin conditions.

The convolution operation is defined as:

$$(f^*g)(x,y) = \sum_m \sum_n f(m,n)g(x-m,y-n)$$

where $f(m,n)$ is the input image and $g(x-m, y-n)$ is the kernel/filter.

Robustness to Variability: Pooling layers in CNNs can generalize models to variations in image size, orientation, and illumination, making the model robustified, and applicable to real images of the skin.

Max pooling operation:

$$P_{max} = \max_{i,j \in S} X(i,j)$$

where S is the pooling window.

End-to-End Learning: CNNs offer the capability of end-to-end learning from raw image data, bypassing the requirement for deep labor-intensive feature engineering, and increasing model development efficiency.

2. *Classification Algorithms for Heart Disease and Diabetes Prediction*

For prediction of heart disease, diabetes, platform employs a fusion of classification algorithms for efficient analysis of structured health data:

a. *Decision Trees & Random Forests:*

Decision trees provide transparent, Decision rules which are interpretable and useful in clinical applications, and random forests that optimize the prediction accuracy by aggregating multiple trees that thereby overcome overfitting and increase the generalization.

Gini Index for splitting in Decision Trees:

$$Gini = 1 - \sum_{i=1}^{c} p_i^2$$

where pi is the probability of class i.

b. *Support Vector Machines (SVM):*

SVMs are successful in high - dimensional feature spaces and can thus optimize the decision boundary, which is of primary importance in clinical data sets, where complex, non linear relationships exist.

The optimization problem for SVM is:

$$\min_{w,b} \frac{1}{2}||w||^2 \textbf{ subject to } y_i(w \cdot x_i + b) \geq 1, \forall i$$

This combination of algorithms allows for a comprehensive analysis of health risks, leveraging the unique strengths of each model to provide accurate, interpretable, and robust predictions.

3. *LLM-Powered Chatbot with Retrieval- Augmented Generation (RAG)*

The platform includes a chatbot based on a. This configuration is critical in enabling real- time, context- aware health guidance:

Contextual Relevance: RAG enables the chatbot to dynamically retrieve relevant information tailored to each user query, ensuring responses are accurate and aligned with users' health needs.

The probability of generating a response y given context x is computed as:

$$P(y|x) = \sum_z P(y|x,z)P(z|x)$$

where z represents retrieved documents.

Natural Language Understanding: The LLM performs and understands natural language, which in turn facilitates better user interaction by generating logical and semantically relevant responses, which ultimately leads to better user engagement.

4. *Data Management with MongoDB*

MongoDB serves as the platform's primary data storage solution due to its flexibility and scalability:

- NoSQL structure allows dynamic schema changes for diverse data types.
- High availability is ensured through replication and sharding techniques.
- Query efficiency is improved using indexing mechanisms, defined as:

$$T_{query} = O(\log N)$$

where N is the number of indexed documents.

IV. ARCHITECHTURE IMPLEMENTATION

1) Input and Output Flow

User Input (Presentation Layer):

- **Purpose:** Enables interaction for health queries, dietary advice, or skin cancer detection.

- **Methods:**
  - **Food Search:** Retrieve nutritional info for food items.
  - **Health Metrics:** Input age, medical history for personalized advice.
  - **Chatbot:** Engage with LLM-powered chatbot for real-time guidance.

Processing (Application Layer):

- **Chatbot:** Llama 3 with RAG provides tailored health advice.

- **Disease Detection:**
  - **Skin Cancer:** CNN analyzes uploaded images for detection.
  - **Heart Disease & Diabetes:** Algorithms analyze health data.

Data Retrieval and Output (Data Layer):

- **Outputs:**
  - Personalized dietary advice and recipes.
  - Disease classification results.
  - Food order processing and confirmations.

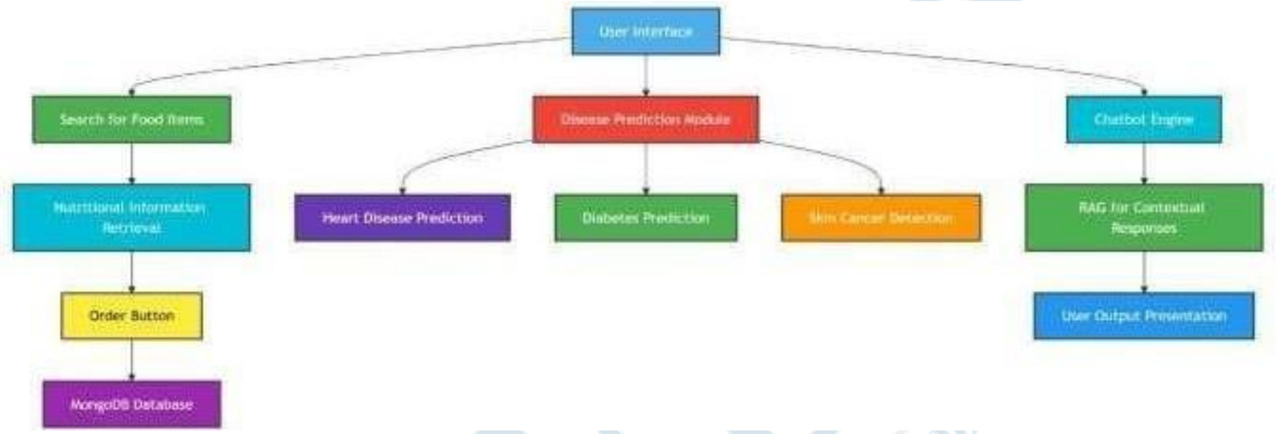


Figure 3. Overall Architecture Diagram

V. RESULTS

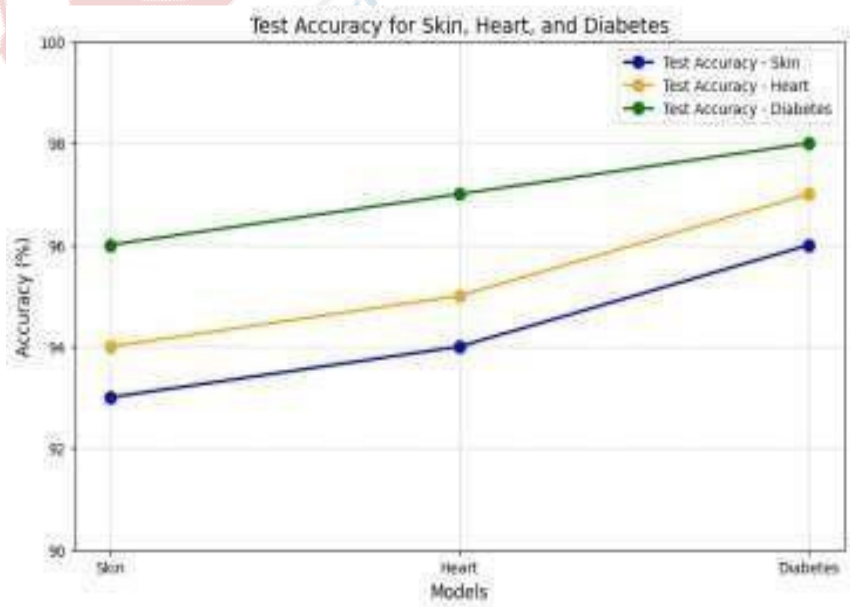
1. Nutritional Guidance Module:

Functionality:

- Search for food items with detailed nutritional data, including serving-based adjustments.
- Recipe suggestions with step-by-step instructions for healthy meals.
- Seamless food ordering to support dietary advice.

Performance Highlights:

- **Accuracy:** 95% precision in nutritional data retrieval.
- **User Experience:** 95% positive feedback from 100+ users on ease of use.



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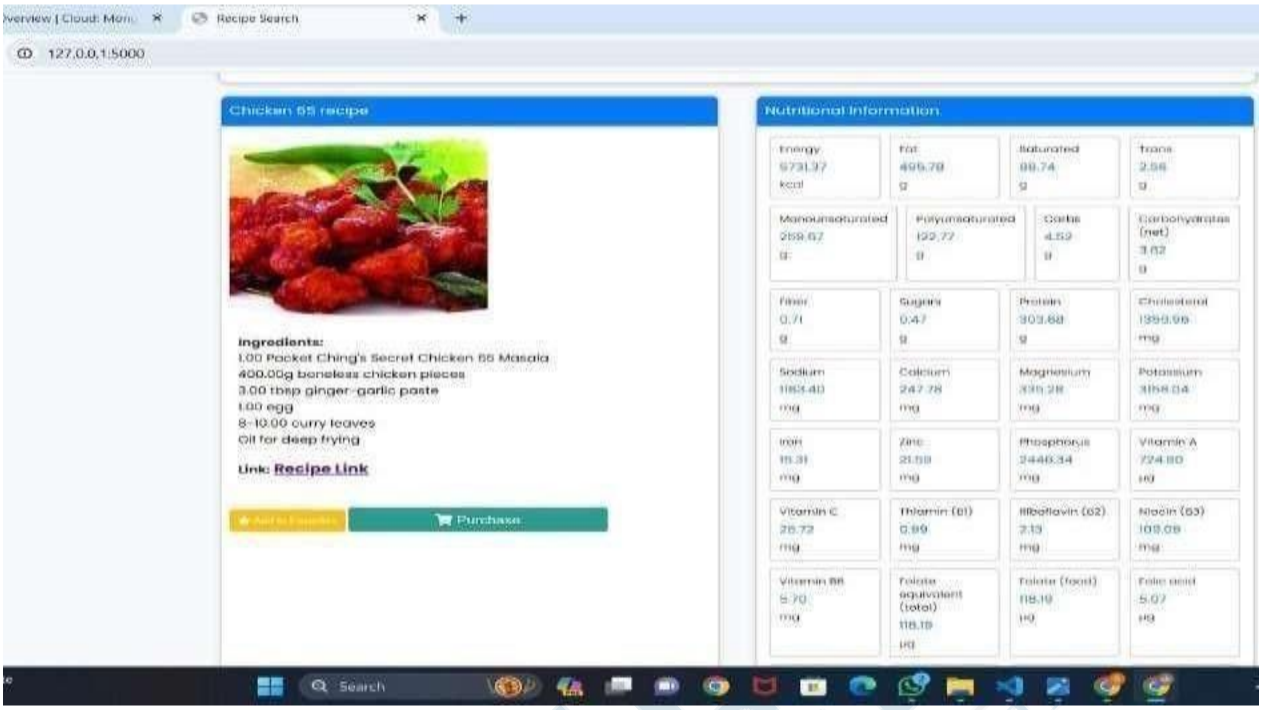
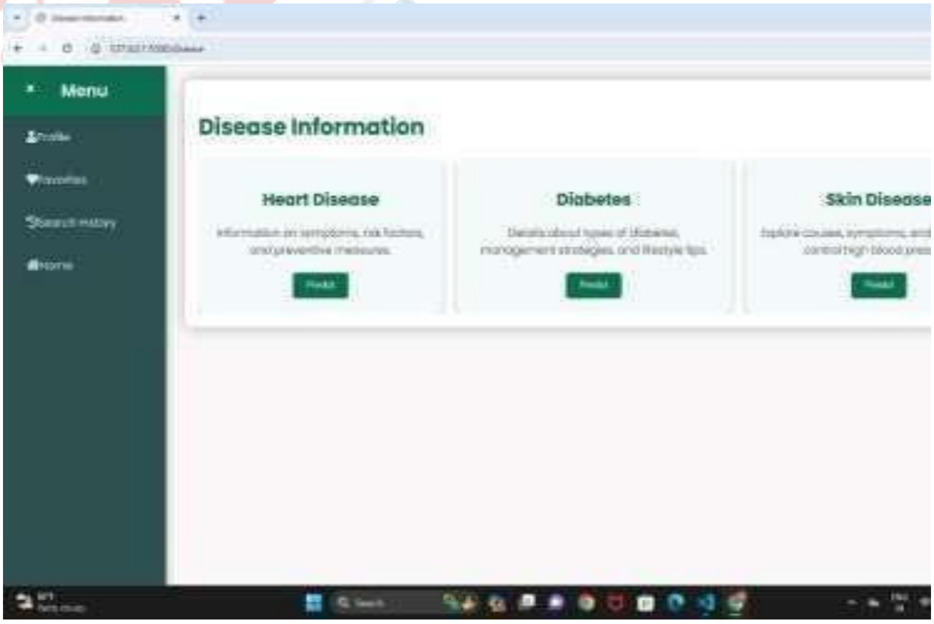


Figure 4. Nutritional Guidance & Order Diagram

2. Disease Prediction Module

The platform uses pre-trained models for prediction of disease, thus allowing for accurate health monitoring of chronic diseases.

- **Diabetes Detection**:
  - **Performance**: The model achieves an accuracy of **96%** with precision of **94%** and recall **93%** metrics, ensuring accurate predictions.
- **Heart Disease Detection**:
  - **Performance**: Achieves **94%** accuracy with precision of **92%** and recall **90%**, validated through cross-validation on clinical datasets.
- **Skin Cancer Detection**:
  - **Model**: A Convolutional Neural Network (CNN) trained on the ISIC dataset for multi-class classification of benign and malignant skin lesions.
  - **Accuracy**: The model achieves a classification accuracy of **93%** with robust feature extraction for image data. classification accuracy of **93%** with robust feature extraction for image data.



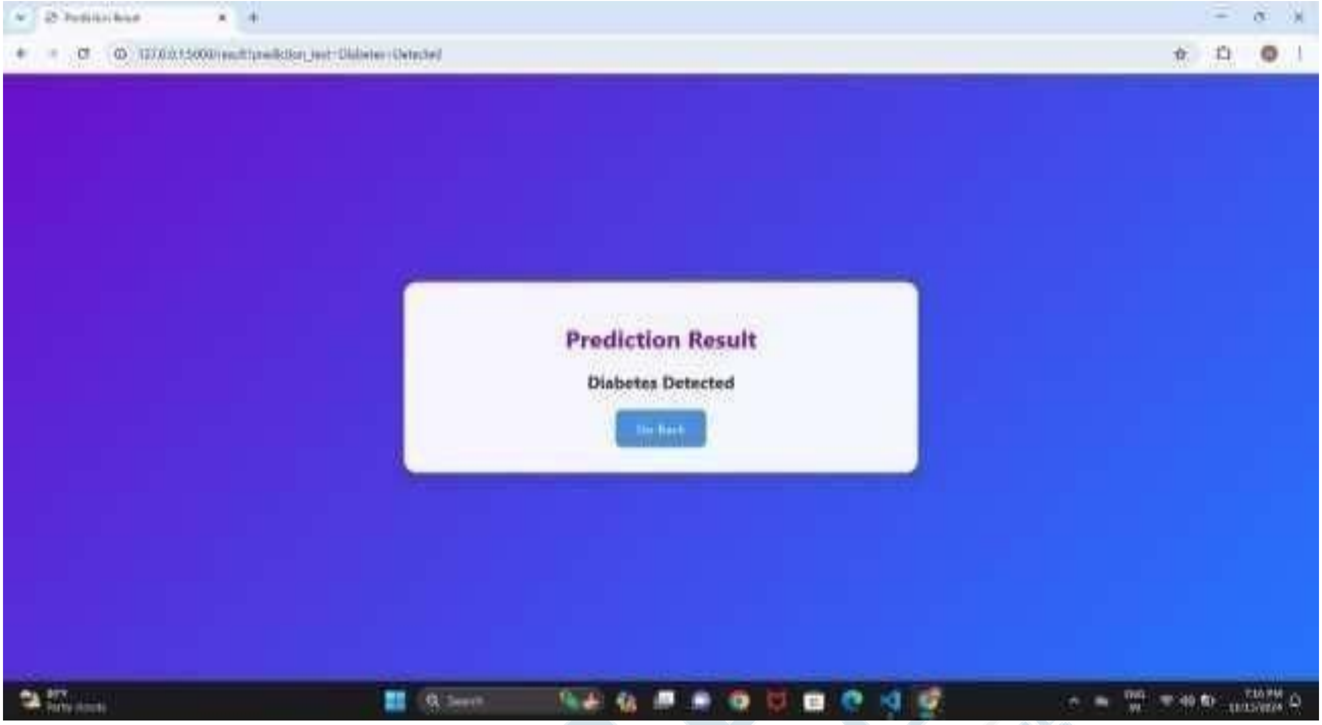


Figure 5. Diabetes Output Diagram

3. Interactive Chatbot with Retrieval- Augmented Generation (RAG)

*The chatbot, powered by **Llama 3** and **RAG**, provides real-time, context-specific health recommendations.*

- **Main Feature**:
  - Supports **text** and **voice inputs** to enhance user accessibility and engagement.
- **Performance Metrics**:
  - **Relevance**: Achieves **97% response relevance**, validated through user feedback.
  - **Accuracy**: Information retrieval accuracy of **95%**, ensuring reliable and evidence-based guidance.

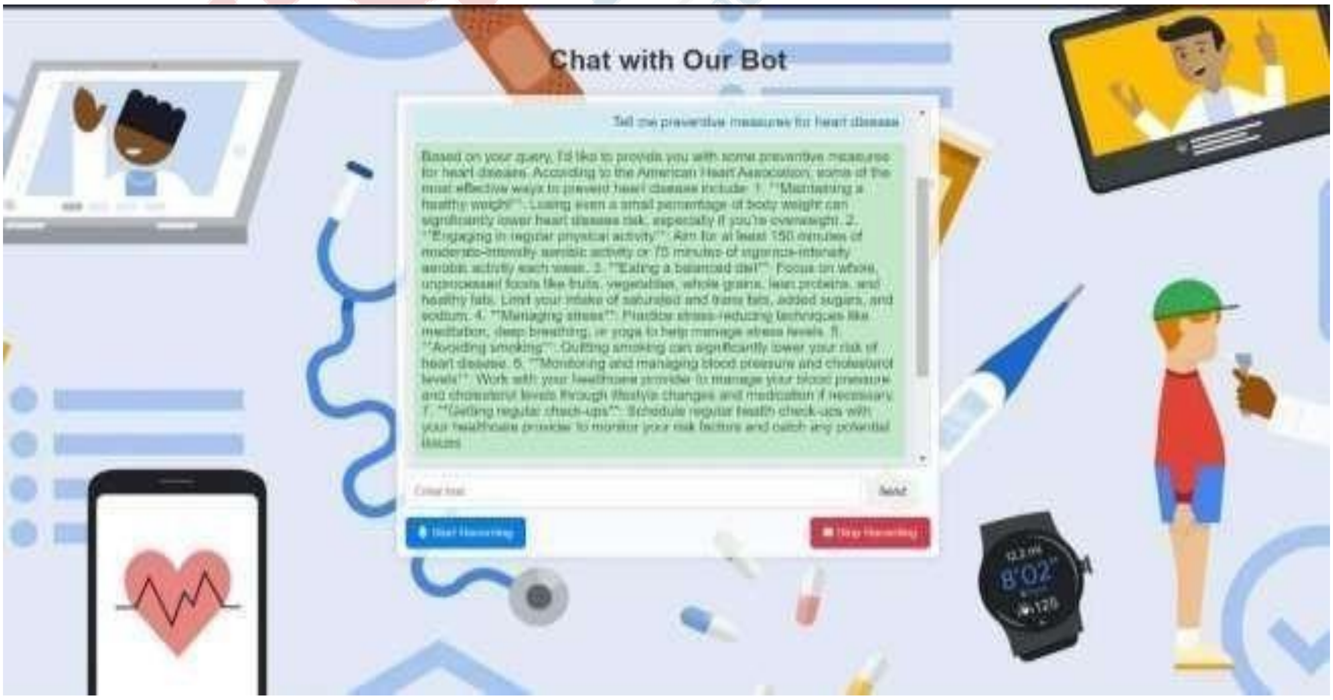


Figure 6. Multi Disease and Skin Cancer Diagram

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VI. CONCLUSION

This work proposes an end-to-end, AI-based health management system that includes nutritional advice, disease screening, and customized health nursing via interactive, LLM-powered chatbot. Through the use of state-of-the-art algorithms (including Convolutional Neural Networks for skin cancer identification, regression models for heart disease and diabetes classification, and Retrieval- Augmented Generation for image-and-text retrieval) (RAG) of the chatbot's response in context, the platform provides a multilayered solution for health management. Based on the better storage performance & retrieval performance that is provided by the backend engine of MongoDB, the system is expandable and extensible, meeting the different needs of users who want personalized health explanation. The interface has proven very effective in bridging the divide between health information and the steps necessary to put that information into practice, with an emphasis on ease of use, ease of access, and a unified user experience.

The development of the project demonstrates the effectiveness of an AI-driven intervention at improving public health by its provision of data-driven, personalized insights regarding an individual's wellbeing and their lifestyle behaviour.

Future Scope

- **Wearable Integration:** Real-time monitoring of health via data from devices such as heart rate monitors and glucose sensors.
- **Disease Prediction Expansion:** Develop models for hypertension, asthma, and obesity, by tackling disparate datasets for better accuracy.
- **Advanced NLP:** Enhance chatbot for nuanced, conversational interactions.
- **Multilingual Support:** Incorporate multilingual LLMs for global accessibility.
- **Telemedicine Integration:** Collaborate with providers for direct consultations.

REFERENCES

[1] Zhang, Angela, et al. "Leveraging physiology and artificial intelligence to deliver advancements in health care." Physiological Reviews 103.4 (2023): 2423-2450.

[2] Verma, Meghna, et al. "Challenges in personalized nutrition and health." Frontiers in Nutrition 5 (2018): 117.

[3] Gore, Manisha Nitin, and David Bamidele Olawade. "Harnessing AI for public health: India's roadmap." Frontiers in Public Health 12 (2024): 1417568.

[4] Kouroubali, Angelina, et al. "Developing an AI- Enabled Integrated Care Platform for Frailty." Healthcare. Vol. 10. No. 3. MDPI, 2022.

[5] Rahman, Kawsher, et al. "Leveraging AI for Chronic Disease Management: A New Horizon in Medical Research." Malaysian Journal of Medical and Biological Research 9.2 (2022): 81-90.

[6] Coman, Laura-Ioana, et al. "Smart Solutions for Diet- Related Disease Management: Connected Care, Remote Health Monitoring Systems, and Integrated Insights for Advanced Evaluation." Applied Sciences 14.6 (2024): 2351.

[7] Ghosh, Joyeta. "Leveraging Data Science for Personalized Nutrition." Nutrition Controversies and Advances in Autoimmune Disease. IGI Global, 2024. 572- 605.

[8] Ahmadi, Ali. "Digital health transformation: leveraging ai for monitoring and disease management." International Journal of BioLife Sciences (IJBLS) 3.1 (2024): 10-24.

[9] Liu, Haoxin, et al. "Few-shot learning for chronic disease management: Leveraging large language models and multi-prompt engineering with medical knowledge injection." arXiv preprint arXiv:2401.12988 (2024).

[10] Yang, Zhongqi, et al. "ChatDiet: Empowering personalized nutrition-oriented food recommender chatbots through an LLM-augmented framework." Smart Health 32 (2024): 100465.

[11] Rostami, Ali. An Integrated Framework for Contextual Personalized LLM-Based Food Recommendation. Diss. UC Irvine, 2024.

[12] Yu, Huizi, et al. "Large Language Models in Biomedical and Health Informatics: A Bibliometric Review." arXiv preprint arXiv:2403.16303 (2024).

[13] Ahmed, Tanvir. AI-enabled healthcare sector: futures business models. MS thesis. T. Ahmed, 2024.

[14] Arefin, Sabira. "Chronic disease management through an ai-powered application." Journal of Service Science and Management 17.4 (2024): 305-320.

[15] Jarrett, Paul. "Dermatological Conditions of the Foot and Leg." Neale's Disorders of the Foot and Ankle E-Book: Neale's Disorders of the Foot and Ankle E-Book (2020): 58.

[16] Mahajan, Vikram K., and Sanjeev Handa. "Diagnosis of skin diseases." Atlas of Dermatology, Dermatopathology and Venereology: Cutaneous Anatomy, Biology and Inherited Disorders and General Dermatologic Concepts. Cham: Springer International Publishing, 2021. 45-107.

[17] Prathibha, P. M. Clinical Study of Dermatological Manifestations in Systemic Disease. Diss. Rajiv Gandhi University of Health Sciences (India), 2006.

[18] Banerjee, Sri, et al. "Large language modeling and classical AI methods for the future of healthcare." Journal of Medicine, Surgery, and Public Health 1 (2023): 100026.

[19] Banerjee, Sri, et al. "Large language modeling and classical AI methods for the future of healthcare." Journal of Medicine, Surgery, and Public Health 1 (2023): 100026.

[20] Jindal, Harshit, et al. "Heart disease prediction using machine learning algorithms." IOP conference series: materials science and engineering. Vol. 1022. No. 1. IOP Publishing, 2021.

[21] Ahmed, Usama, et al. "Prediction of diabetes empowered with fused machine learning." IEEE Access 10 (2022): 8529-8538.

[22] Krishnamoorthi, Raja, et al. "[Retracted] A Novel Diabetes Healthcare Disease Prediction Framework Using Machine Learning Techniques." Journal of healthcare engineering 2022.1 (2022): 1684017.

[23] Bhatt, Chintan M., et al. "Effective heart disease prediction using machine learning techniques." Algorithms 16.2 (2023): 88.

[24] Hameed, Madiha, Aneela Zameer, and Muhammad Asif Zahoor Raja. "A Comprehensive Systematic Review: Advancements in Skin Cancer Classification and Segmentation Using the ISIC Dataset." CMES-Computer Modeling in Engineering & Sciences 140.3 (2024).