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Personalized Food Recommendation based on Disease and Food Image Analysis

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***Abstract*— Choosing food correctly is a factor and in most times challenging to the patients having conditions of diabetes, high blood pressure, celiac disease or food allergies, particularly in situations where the information was not provided on the ingredients. The proposed project will provide web based services to inform individuals about the appropriateness of certain type of food in relation to their health conditions. Convolutional Neural Network(CNN) identifies the food on the images when the clients upload their food on the site. This is then succeeded by the analysis of food and health conditions of the user using a Large Language Model(LLM) to give a clear answer with regards to the safety, risk, and healthier option. It is built with secure logins, custom dashboard to check past analysis, fully furnished back end on the foundation of Node.js and Express and the present front end on the foundation of Next.js. With the help of such technologies, the project proves that AI can improve the food preferences of any individual in their everyday life and make them healthier and better informed about the food.**

***Index Terms*— Food recognition, Convolutional Neural Network, Large Language Model, dietary recommendations, health monitoring, personalized nutrition, web-based application, AI-assisted diet guidance.**

I. INTRODUCTION

The food preference of the individuals is not merely dictated by the food habits of the individuals who have diseases such as diabetes, blood pressure, celiac disease or even allergies of food but it also rests on the overall health of the individuals. Healthy eating is a frustrating experience, as one may not know what to eat or work with something the contents of which are unknown. To facilitate this we have made an web application (NutriScan) which will enable the user to scan an image of any food and will provide a quick and personal response of whether the food is healthy or not. The platform identifies the food in the uploaded photo and then checks its suitability based on the user's medical condition provided during input.

The classifier was used to conduct the training process of 4,000 images (about 90 varieties of cuisines). It can detect food items like biryani, idly, shrikand etc properly. Once the food item is identified, the system will decide on whether the item should be consumed or avoided according to the medical condition of the user. The food will be categorized and retrieval of data with analysis of medical condition of the user will be carried out under the LLM and provides alternatives if it is not suitable to the user.

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This is achieved through inclusion of different user friendly features in order to make it easier to operate. The secure authentication allows every user to possess a unique account to him or her within the application. When the user logs in, a dashboard showing their past scan data and analysis results is displayed. This helps users track their eating habits and review their previous meals. The system does not provide just binary results. It provides the context, it holds the user specific information and provides choice. The application is built based on the existing web technologies, Next.js as the front-end platform, and Node.js with Express as a web server. Session data are being stored using MongoDB and secure sessions are being offered through the use of HTTP-only signed cookies. MongoDB has been used to store the session information and HTTP-only signed cookies have been used to issue secure sessions.

This project will focus on ensuring that the food choice is a smoother and better process than individuals whose dieting needs are specific. It integrates the system which can be interpreted as bridging the gap between clinical problems applied by healthcare and artificial intelligence through machine learning, language models, full-stack development. This is a strategy to make sure that the quality of the life of the people in question is put into consideration in a bid to make them consume less and healthier.

II. RELATED WORK

Among the categories of computer-based food system that have been widely gaining popularity is recommended food systems among people with problems regarding their health such as diabetes, high blood pressure and allergies. These are technologies that can be used to demarcation of a wide range of primitive rule-based filters to advanced machine learning to allow customers to make smarter food choices. The current project has been developed based on the previous research.

A case in point, Longqi Yang and et. al have come up with a kind of meal recommendation system, the Yum-me, which is not only cognizant of the nutrient value, it also acquaints itself with the tastes of the users via a visual test. The study they carried out revealed that the recommendation customizations could boost the satisfaction level by more than 42 points, especially in persons whose diets were restricted [1].

In the same vein, Raksha Pawar and Shazia Lardkhan came up with NutriCure that applies KNN algorithm to provide the diet plan in accordance with the medical needs of an individual. With its simplicity and simplicity of use, NutriCure was not organized in terms of data and failed to follow the key health indicators such as BMI/BMR, which is why it was desperate when performance issues were concerned in terms of precision and accuracy. personalization [2].

The paper by T. Muke et. al proposed a food recommendation system tailored to health disorders using machine learning techniques like K-means clustering, Random Forest classification, and collaborative filtering, this system suggested diet options that improve immunity and match individual health needs, especially relevant during the COVID-19[3]

Yera et. al emphasized the significance of transparent suggestions by pointing out limitations such tiny datasets, little real-world testing, and a lack of explainable AI [4].

For diabetic food recommendations, Anjankar et al. suggested a system that uses Random Forest and Linear Regression. However, it mostly depended on precise user input, like BMI, which isn't always available. This led to the investigation of more approachable methods, such as image recognition [5].

MATURE-Food is the system that is launched by Ritu Shandilya and et. al in order to assist people with strict diet. They were not accurate in reporting but in order to alleviate the chronic illnesses, they used the classification and similarity algorithms in ranking the vital nutrients and that was very convenient [6].

Another solution worth mentioning is that of S. Gupta and et. al, DIAFOODS. This Random Forest based solution on diabetic patients was highly accurate (96.57 percent), which provided much needed and customized diet advice in regions with elevated diabetes levels [7].

To tailor the meal plans, Balaji and Nagarajan adopted content-based filtering algorithm, where the food choices were aligned with the individual calorie and nutrient needs of the people [8].

Singh and Bhatnagar assert that modern diet recommendation systems are increasingly successful by integrating machine learning, collaborative filtering, and hybrid implementations to offer personalized nutrition advice [9].

In order to improve meal recommendations, Bian, Xie, and Lu stressed the significance of context-aware recommendation, taking into account variables including time, location, activity level, and health state [10].

Dalakleidi et al. highlighted the growing importance of food recognition through images to automated dietary measurement. Likewise, the nutritional calculations based on the food photos and text were examined by Mezgec and et. al through the combination of deep learning and natural language processing [11][12].

The CNNs, transformers, and multimodal models are currently better at recognizing dishes with complex recipes and predicting the size of portions, as shown by the survey of deep learning related advancement in food image recognition conducted by Liang and colleagues [13].
Crystal, Yasin, and Jagan showed smartphone based food classifiers that are able to assess nutrients and estimate portions in three dimensions, which is especially beneficial in managing diabetes [14].
CNNs outperform the traditional image detection methods as they automatically extract the most important image attributes that serve in the identification of food as illustrated by Kagaya et al. [15].
Liang, Gu, and Zhang developed a simple, straight forward, and easy-to-understand approach to real-time food recognition on a mobile device using CNNs and Vision Transformers [16].
Zhao and colleagues improved the prediction of nutrients on the basis of food images through a combination of image segmentation and regression analysis, which allowed better predicting calories, carbohydrates, fat and protein [17].
Zhang, Li and Wang investigated how the combination of language-based models and image analysis can be used to come up with context sensitive meal suggestions, especially to individuals with chronic kidney disease [18].
An AI-based Mediterranean diet recommender that used machine learning and nutritional guidelines to guarantee balanced, culturally appropriate meal recommendations tested by Kalpakoglou et al. [19].
Lastly, Belkhouribchia and Pen tested large language models in clinical nutrition and found out that such models could be useful in nutrition counseling, meal planning, and diet-related medical advice, and make it more accessible and supportive to decision-making [20].
Table I shows the Comparative analysis of the existing food recommender system and the NutriScan developed project.

TABLE I: COMPARATIVE ANALYSIS

Author(s)	Method / Technique Used	Key Contribution	Limitations Identified	NutriScan
H. Yang, J. H. Lee, and J. Kim	Nutrient-driven recommender using visual quiz for preference elicitation	Captures user food preferences through image selection; integrates visual preference learning with nutrient matching	Does not include medical conditions or disease-specific diets	Includes Medical conditions those overcomes the limitation
A. Anjankar et al.,	Health-condition based filtering; K-Nearest Neighbors classifier on a custom nutrition dataset	Generates diet plans using user health conditions, medical restrictions, and stated preferences	No accuracy/F1 metrics reported; performance and model robustness not quantified No multi-modal inputs (text + image)	Multi-modal input (image + text) solves their single-mode limitation.
R. Shandilya, A. Verma et,al	Content based system using mandatory nutrient constraints + similarity based matching algorithms	Ensures required nutrients (e.g., for chronic disease patients) are included even if foods are unfamiliar to users	Reported to "perform well" in clinical scenarios, but no numeric accuracy results provided. No image input	Uses image input, improving preference learning drastically.
S. Gupta and K. Yadav	Content-based recommendation + Random Forest classifier for diabetes level prediction	Provides diabetic-specific food recommendations by predicting diabetic level and filtering foods accordingly	No image input, restricted for diabetes, Model is predicting only the level of diabetes.	Uses image input, Generalized for different chronic diseases, Language model provides recommendation

III. METHODOLOGY

This project was developed in an organized fashion with the goal of creating a dependable and user-friendly food recognition and recommendation system specifically designed for people with chronic illnesses. As explained below, the work was carried out in four main stages.

A. Data Collection and Preprocessing

The first phase involved them gathering 4,000 images of Indian food available in 80-90 categories that were famous. The pictures were marked with the name of the foods. The classification model has been made with this labelled dataset. To encourage the highest possible learning of the model all the images were rescaled to the normalized standard input scale which was appropriate to the model and the images were also rescaled to have equal pixel intensities. Generalization process was enhanced by using data augmentation techniques, such as rotation, flipping, and zooming.

B. Machine Learning Implementation

A CNN was trained to identify the uploaded food photos. CNN architecture suits image identification activities most aptly due to the capacity to reason about complex visual arrangements. To prevent overfitting, the model configurations were experimented on different levels of convolutional layers and filters, learning rates, batch and dropout rates. CNN also did a good job at distinguishing various types of food but it required additional data to explain whether a particular meal can be healthy to a patient with given condition. After the CNN understands what is on the plate, the LLM will match it with the health condition of the user, and it generates easy-to-understand explanations and also suggests healthier alternatives. The combination of contextual reasoning and visual identification, CNN and LLM improved the system's performance and increased its suitability for health-based food analysis.

C. Backend and Frontend Development

The project was built as a full-stack web application with the backend based on Node.js and Express.js, which performs user sessions, models integration, and necessary features. The frontend built using Next.js provides a responsive and fluid user experience. The user interface is simple in design, which allows users to register, log in, and upload photos of foods easily. The technology scans every image uploaded and shows the results in a comprehensible way. The security of the user data was ensured with the help of the session-based authentication with signed cookies that ensured that all the information is private and only the authorized user can see it.

D. Additional Features

Several new features were introduced in order to make it more useful and practical. The system gave safer alternatives to a food item in case it is unsuitable to the user. The ability to track the evolution of their eating habits is possible because of the user history feature, which leaves a record of all the uploads with the results that accompany them. Also, the system offers brief descriptions of the possible health impacts of any food option. Such advancements address the gaps of the previous studies that often did not possess the features such as tracking the food which was earlier searched, explainability, or personalization.

E. System Design Overview

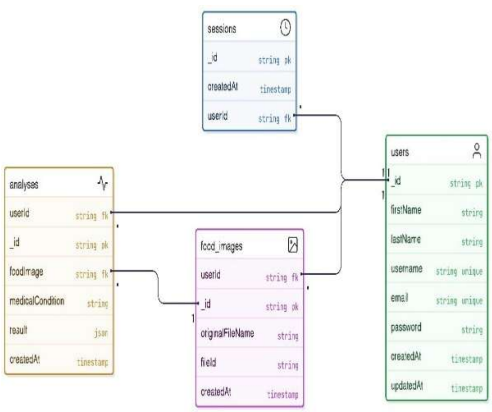

Fig. 1: Entity Relationship Diagram of the System

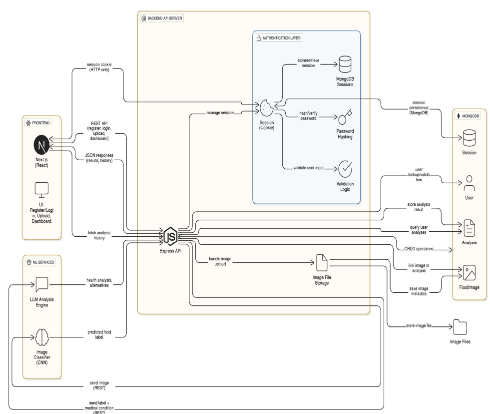

Fig. 2: System Workflow

The architectural design and system interactions are illustrated through two diagrams. The Entity Relationship (ER) Diagram, which is used for backend schema design, is depicted in Fig. 1. It shows how entities like users, health profiles, and food photos relate to recommendations and prediction outcomes. The entire system workflow, including image upload, CNN classification, LLM reasoning, and final output generation, is shown in Fig. 2.

IV. Results and Discussion

The results indicate that users can easily get the guidance on nutritional analysis from the simple interface of NutriScan. The fact that the system is not complex is one of its key strengths; the intricate instructions can be adhered by even the individuals who lack technical knowledge. It will be easy to upload an image and understand the results to first time users. Another valuable benefit is the real-time feedback that the LLM provides to brief the explanations about the suitability of food, potential health hazards and alternatives to food. The history tracking feature can further assist users since it allows users to review past scans of the food, monitor the eating habits, and make improved choices. The system also calculates the calories of each item identified, nutritional value, specific data such as sodium, potassium, and other significant nutrients of every 100 grams, to make the user more aware of their food choices. Although these features are of great value, they still can be improved. The approach to multilingual assistance would assist in reaching more people, and voice-based interaction would make the system more accessible to those visually impaired or aged. Overall, NutriScan is successful in fulfilling its primary goal of being user friendly, educative and promoting healthier eating habits. It also provides opportunities of improvements in future intelligence and availability. Certain problems still remain such as the multi class classification of the CNN which has resulted in some food categories identified inaccurately. The overall accuracy of the model that was achieved through averaging all the classes was found to be 67 percentage. Table II is a summary of the overall performance of the model, Figure 4 shows the confusion matrix, and Figure 3 shows the average precision, recall, and F1-score.

TABLE II: NUTRISCAN CNN CLASSIFIER PERFORMANCE

Metric	Value
Test Accuracy	67.00%
Loss (Test)	1.25
Recall	67.00%
Precision	70.90%
F1-Score	67.42%

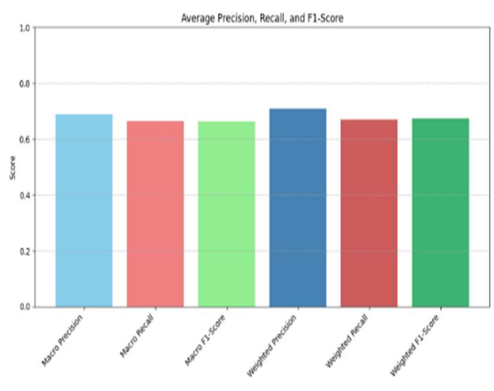

Fig. 3: Average Precision, Recall and F1-Score

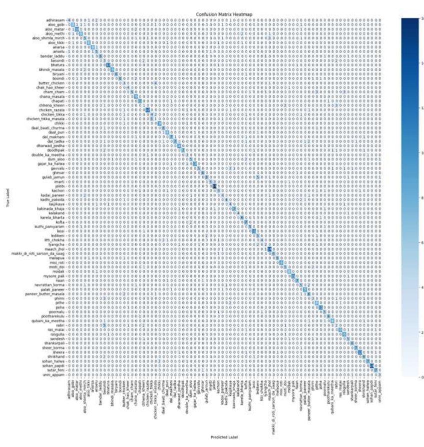

Fig. 4: Confusion matrix heatmap

V. ETHICAL AND PRIVACY CONSIDERATIONS

Because of the sensitivity of dietary and personal health information, NutriScan deals with the need to safeguard the privacy. All user profiles and dietary histories are stored securely and processed only with informed consent. Personal information such as food allergies and diabetic condition of the users is not disclosed to anyone.

VI. CONCLUSION

The main aim of the given project is to help the individuals with the medical problems such as diabetes, blood pressure or allergies to the food to make the right and healthier food choice. This system has been created to be multidimensional system, sensitive to the suitability of each food to the medical requirement, although at first was to find out the type of food by photo. The system will also provide intelligent and helpful recommendations and integrate CNN with LLM to be familiar with the dietary requirements. The modern web technologies (Next.js and Node.js) are applied in practice to enhance the reliability, availability, and functionality of the system and ensure the safety of session management with a convenient user interface. It can also be improved in the future in several aspects. There is also the possibility that the ingredient level identification will provide the user with more restrictive dietary restrictions considering the ingredients being defined as sugar, salt, or oil. It is also possible to assume that more accuracy would be achieved as the datasets would also be extended. Furthermore, creating a specialized mobile application would enable consumers to rapidly evaluate food suitability when dining out, grocery shopping, or cooking at home. The system's practical utility would be greatly increased by these improvements, making it a dependable digital health assistant for everyday usage.

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