Nutrition Management System

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Abstract. WHO recognizes the increase in various non-communicable diseases in today's world that people face, such as type 2 diabetes, digestive diseases, kidney diseases, weight management, and blood diseases, due to the inability to maintain a healthy diet. Owing to various factors like lack of nutritional knowledge, busy lifestyles, lack of motivation, easy access to fast food, or preferability over healthy food. The Nutrition Management System is a website designed to recommend personalized meals based on their health conditions. This system prompts users to upload their health reports, from which key values are extracted using Optical Character Recognition process and appropriate meals are recommended using machine learning algorithms. The Decision Tree machine learning algorithm has been selected due to simplicity, efficiency, and suitability in healthcare applications. The objective is to inculcate healthy eating habits, decrease ailments caused due to lifestyle and help individuals improve their health and wellbeing.

Keywords: Nutrition Management, Machine Learning, Decision Tree Algorithm, Health Report Analysis, Optical Character Recognition (OCR), Allergy-Based filtering, Personalized Meal Recommendations.

1 Introduction

In today’s world, it has become very challenging to follow a healthy lifestyle especially for those suffering from chronic issues like diabetes, cholesterol, and nutritional deficiencies. Getting regular health check-ups can give you valuable insights but it can be complicated to decide what diet to follow. The Nutrition Management System effectively addresses this challenge by using Optical Character Recognition (OCR) combined with machine learning algorithms to generate customized meals. People can upload their health report and key health values like sugar, cholesterol, haemoglobin values will be extracted automatically. These values are then compared with the standard medical ranges. This data is then used to provide health specific personalized nutritional meals. This system also considers allergy-based filtering and recommends meals as per users’ allergies. This paper mainly presents the methodology, architecture, and results of the nutrition management system and shows how smart nutrition planning can be achieved through machine learning algorithms.

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2 Literature Review

Recent advancements have resulted in various diet recommendation systems for different health and nutritional goals. As part of weight loss strategies, calorie deficit, macronutrient ratio, and meal timing all significantly contribute, as per the study in [1]. No single diet plan can work for everyone, so diets like low-carb, intermittent fasting, and mindful eating should be personalized. But these strategies are mainly about weight and not about your current health data.

To tackle disease-specific nutrition, [2] proposed an IoMT-based recommendation system using LSTM, GRU deep learning models. It considered age, weight and nutrients but depending on a static dataset.

In [3], a model using fuzzy logic and collaborative filtering was proposed that recommends meals based on BMI, allergies, and food preferences, but which required data input manually.

In another model discussed in [4], K-means and Random Forest algorithms were employed to propose meals for deficiencies such as anaemia and goitre. However, this model also necessitated user entry of health-related data.

The system described in [5] used graph traversal techniques on 345 lab reports and more than 3,400 food items. It provided meal recommendations based on pathology reports but still relied on manual entry of reports.

In contrary, the suggested nutrition management system is completely automatic. It pulls out the health values from the user-uploaded report using OCR and uses ML to suggest related meals. Thus, further manual entry is not required by the user. It also allows for filtering and offers a practical and smart solution for real-time, condition-based nutrition planning.

3 Methodology

3.1 About the Dataset

The dataset for micronutrient data, as shown in Fig. 1, consists of 523 food items. The columns display their nutritional values, including aluminium, arsenic, cadmium, calcium, chromium, cobalt, iron, lead, lithium, magnesium corresponding to the food item. The dataset for macronutrient data, as shown in Fig. 2, consists of 152 food items. The columns display their nutritional values, including moisture, protein, fat, fibre, carbohydrates. Both these datasets are taken from the Indian Food Composition Table [6].

3.2 OCR and Health Report Data Extraction

The system uses optical character recognition (OCR) via Tesseract, an OCR engine that extracts text from images by converting printed or handwritten text into machine-readable format. Tesseract is used here to extract key parameters from portable network graphics (PNG) images of user health reports. The extracted content is parsed using regular expressions, identifying key medical parameters: cholesterol, sugar, and haemoglobin. These extracted values are then passed on for visual nutrition tracking and classification using machine learning algorithms, as shown in Fig. 3.

food_cod	food_nam	aluminum	arsenic_u	cadmium_	calcium_n	chromium
A001	Amaranth	3.32			181	1.227
A002	Amaranth	2.73		0.001	162	0.092
A003	Bajra (Per	2.21	0.97	0.003	27.35	0.025
A004	Barley (Hc	28.64				0.029
A005	Jowar (So	2.56	1.53	0.002	27.6	0.01
A006	Maize, dry	2.82	8.91			0.01
A007	Maize, ter	0.12			6.35	0.004
A008	Maize, ter	0.11			6.37	0.002
A009	Quinoa (C	0.03		0.002	198	
A010	Ragi (Eleu	3.64		0.004	364	0.032
A011	Rice flake	2.44		0.002	9.19	0.05
A012	Rice puffe	2.41		0.004	15.09	0.028
A013	Rice, raw,	0.6		0.002	10.93	0.005
A014	Rice, parb	0.2		0.002	8.11	0.005

Fig. 1. Dataset used for micronutrient data.

food_cod	food_nam	num_regi	moisture	protein	ash	total_fat	dietary_fi
A001	Amaranth	1	9.89	14.59	2.78	5.74	7.02
A002	Amaranth	6	9.2	13.27	3.05	5.56	7.47
A003	Bajra (Per	6	8.97	10.96	1.37	5.43	11.49
A004	Barley (Hc	6	9.77	10.94	1.06	1.3	15.64
A005	Jowar (Soı	6	9.01	9.97	1.39	1.73	10.22
A006	Maize, dry	6	9.26	8.8	1.17	3.77	12.24
A007	Maize, ter	6	68.29	3.57	0.38	1.4	3.67
A008	Maize, ter	4	74.4	4.16	0.36	1.35	3.3
A009	Quinoa (C	1	10.43	13.11	2.65	5.5	14.66
A010	Ragi (Eleu	5	10.89	7.16	2.04	1.92	11.18
A011	Rice flake	6	10.36	7.44	0.85	1.14	3.46
A012	Rice puffe	6	9.4	7.47	1.28	1.62	2.56
A013	Rice, raw,	6	9.33	9.16	1.04	1.24	4.43
A014	Rice, parb	6	10.09	7.81	0.65	0.55	3.74
A015	Rice, raw,	6	9.93	7.94	0.56	0.52	2.81
A016	Samai (Pa	6	11.36	10.13	1.34	3.89	7.72

Fig. 2. Dataset used for macronutrient data.

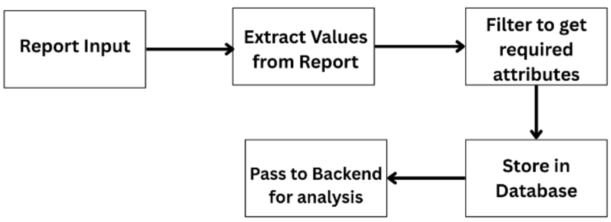


Fig. 3. Report Analysis Workflow.

3.3 Machine Learning-Based Meal Planning

The extracted health values are compared with medically accepted standard ranges of the parameter's cholesterol, sugar, and haemoglobin to identify deficiencies. This system mainly uses a decision tree classifier from the Scikit-learn library to get insights from the data and generate meals. Output meals are recommended for Breakfast, Lunch, and dinner with the help of a curated nutritional dataset. The decision tree algorithm is trained using a labelled nutritional dataset where each row represents a combination of health metrics mapped to a dietary category. Here, internal nodes are for health conditions (e.g., haemoglobin<12), and leaves correspond to specific meal types. This form of structured decision-making allows the system to simulate expert dietary reasoning mechanisms and adapt to various user profiles.

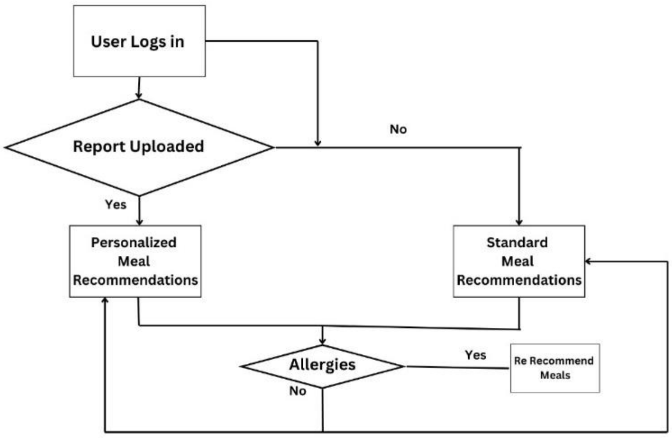


Fig. 4. Meal Recommendation Workflow.

3.4 Allergy-based filtering

To ensure user safety, allergy-based filtering is an option where users have the option to specify the ingredient, they are allergic to (e.g.: nuts, sugar, dairy). These inputs are stored in a database and referenced during meal recommendations. When meals are recommended based on health conditions, the system checks the ingredient list of each user's allergy profile. A meal containing any allergens from that list is automatically excluded from final meal recommendations. The complete meal recommendation workflow is illustrated in Fig. 4.

3.5 Visual Nutrition tracking

This system includes a user-friendly visual feature that displays nutritional values after the report has been uploaded in the form of bar graphs. These graphs represent key parameters such as cholesterol, sugar, and haemoglobin. A table with the standard values of parameters will be displayed below for users to compare with bar graphs. This visual helps users to quickly interpret the values of the report without having to read the full report.

4 System Architecture

This section is focused on presenting the system architecture of the Nutrition Management System based on allergies and Health reports. This architecture shown in Fig. 5, consists of 5 main components each responsible for a key phase in data flow, from data input to final recommendation. These 5 components are:

4.1 User input component

This component is responsible for gathering key health-oriented data from users to start the recommendation process

In this system, there are two main inputs: the health report and allergy information. Additionally, the height and weight of users are taken to calculate Body Mass Index (BMI), allowing them to view their BMI values. The uploaded report consists of critical health parameters like cholesterol, sugar, and haemoglobin, which are then stored for later classification of meals.

4.2 Health reports processing component

This component is responsible for extracting key health parameters for the user health reports using optical character recognition (OCR) via Tesseract and converting image-based reports to machine-readable text. This extracted text is compared with relevant medical parameters like Cholesterol, sugar, and haemoglobin. These values are then retrieved and stored in a Supa base database. This component ensures proper access to essential health parameters and serves as the foundation for personalized meal recommendations.

4.3 Personalized meal recommendations component

This component leverages health data stored in Supa base to generate personalized meal recommendations. After this a decision tree classifier analyses this data and breaks it down into nodes representing thresholds and dietary guidelines, it then classifies meals based on a curated nutritional dataset by comparing them with user health values (e.g.: if cholesterol is high then the system avoids food rich in saturated fats). This model is trained based on this nutritional dataset and personalized meal plans for breakfast, lunch, and dinner are generated.

4.4 Backend and workflow

The backend is developed using Flask, a lightweight and efficient framework in Python. Flask acts like a central controller managing interactions between the frontend, the machine learning model, and databases. Once health data is stored the decision tree classifier using Scikit-Learn is triggered. It handles user requests, interacts with the machine learning model, and delivers the final meal recommendations in a structured format. The backend built on Flask-python ensures smooth data flow, handles Application Programming Interface (API) calls efficiently and provide personalized meals powered by machine learning.

4.5 Frontend

The system's front end is designed using React which is a JavaScript library mostly used for developing web user interface. It is a user interface through which a user can directly interact or work with the system, like uploading health reports, checking nutrition graphs, and looking at personalized meals. For styling purposes, we use Tailwind CSS. The React component communicates with the Flask backend through secure API requests to fetch Health Data, prediction results, and user data in Supa base. The interface consists of an easy-to-use BMI calculator, a report upload section, real time display of report values and suggesting meals-based report values. The system guarantees a consistent layout and spacing with Tailwind CSS, while React ensures a smooth and interactive user experience. The combination of React JS and Tailwind CSS makes the application functionally competent along with beautiful interface.

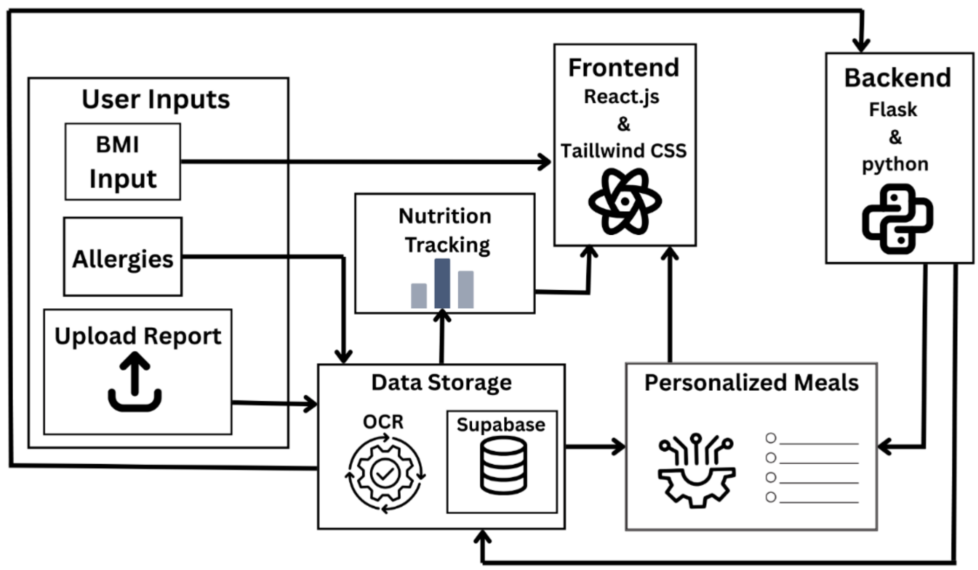


Fig. 5. System Architecture.

5 Results

5.1 Health report upload and tracking

Fig. 6 shows the upload report interface where users upload their health reports and view the health parameter from the reports plotted, I bar graphs along with a table that consists of standard ranges of these parameters. Below the upload report interface is a box provided where users can input food items, they are allergic to.

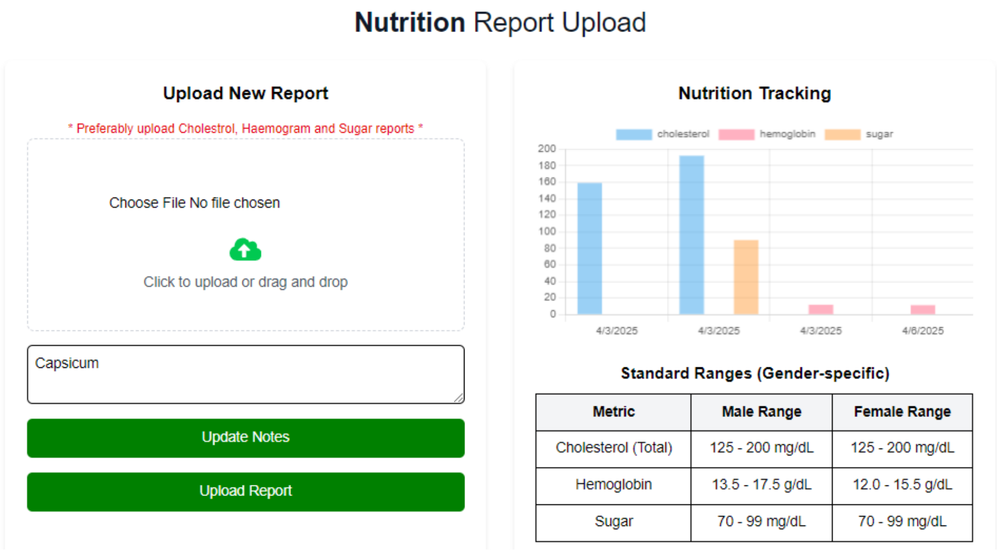
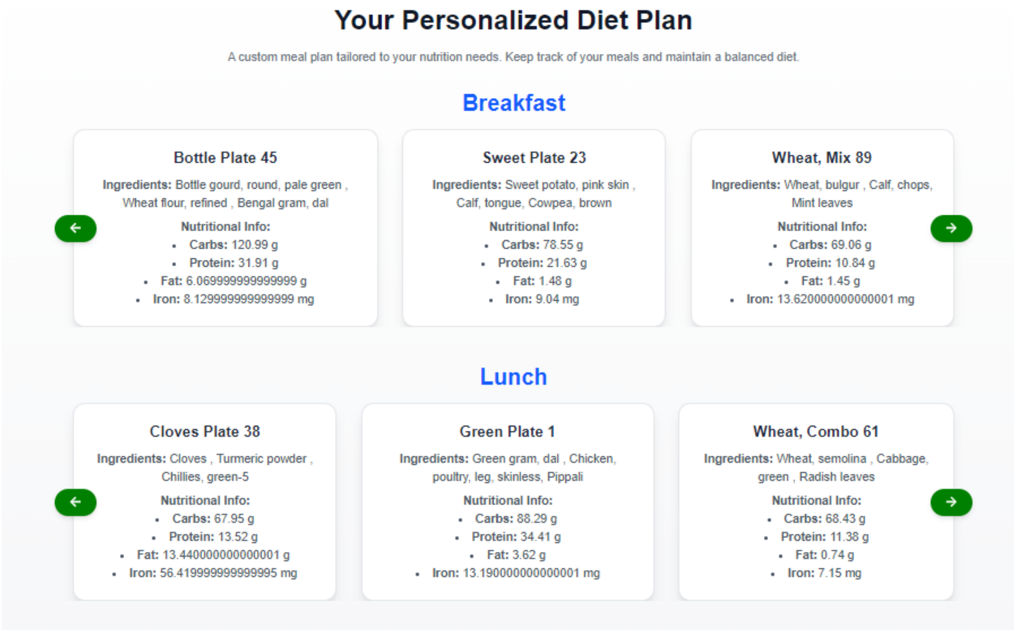


Fig. 6. Report Upload Page.

5.2 Personalized Meal Recommendations

Based on user health parameters with the help of a decision tree classifier, meals categorized as breakfast, lunch, and dinner are recommended along with their nutritional information as shown in Fig.7.



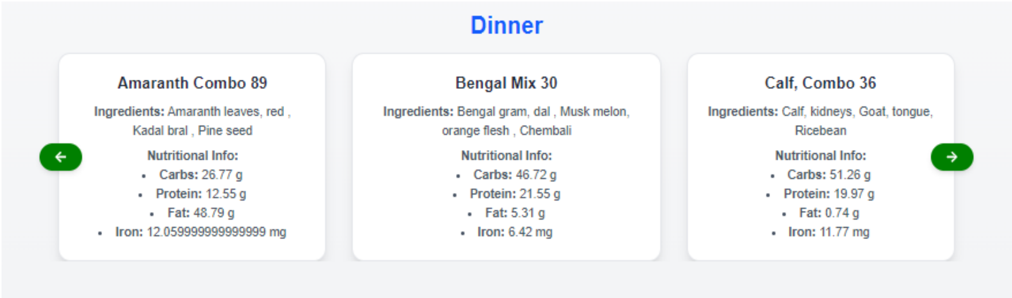


Fig. 7. Personalized Meal Recommendations Page.

6 Discussions

The decision tree classifier, as shown in Fig. 8, achieved an accuracy of 100% on the test set consisting of 105 samples out of 523 items. While this may appear to show excellent results, such perfect results are not common and indicate a case of overfitting. This case of overfitting occurs when a model learns the training data too well, including noise or other patterns, and does not generalize to new data. Hence, this model may perform well on known or similar data but fail to maintain this performance for unseen inputs. This behaviour is further shown in Fig. 9, which shows a clear gap between the training and cross-validation accuracy (~82%), which indicates the model's limited generalization capability.

```
Loaded 523 unique food items.

Decision Tree Accuracy: 100.00% on 105 test samples.
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Fig. 8. Test accuracy of decision tree.

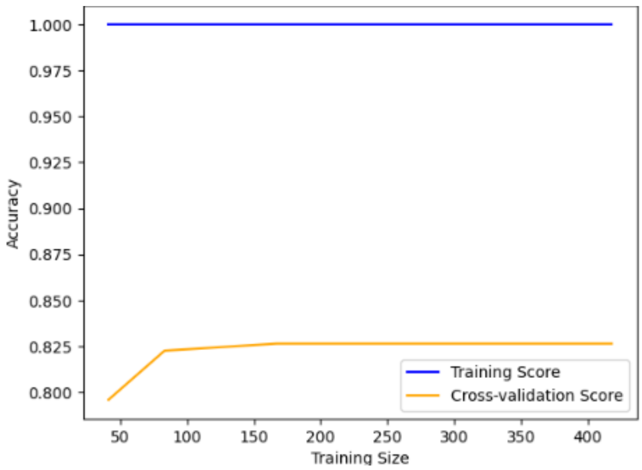

Fig. 9. Graph showing Training and Cross-validation Score.

7 Conclusion

This paper presented a Nutrition Management system that demonstrates how health data can be taken and used to generate personalized meals based on machine learning algorithms, specifically decision trees. By extracting key nutritional parameters from health reports, this system identifies deficiencies and recommends meals based on nutritional needs. Additional features like allergy consideration and visual nutrition tracking further improve user safety and engagement. Although high accuracy was observed, future work should address potential overfitting by expanding the dataset and incorporating better techniques. In the future, the system can be extended to analyse and recommend meals based on more health parameters other than cholesterol, sugar, and haemoglobin.

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