

AI DIET CONSULTANT MANAGEMENT SYSTEM

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Abstract— Personalized nutrition has emerged as a critical component of preventive healthcare and healthy lifestyle management, enabling dietary guidance tailored to individual physiological characteristics and behavioral patterns. Conventional diet planning approaches are labor intensive, generalized in nature, and often fail to accommodate variations in metabolism, body composition, and activity levels. An intelligent AI Diet Consultant framework was developed using a nutrition dataset containing 10,726 records with demographic, anthropometric, and lifestyle attributes, including age, gender, weight, height, physical activity level, body mass index (BMI), and basal metabolic rate (BMR). Data preprocessing involved missing value handling, normalization, feature extraction, BMI and BMR computation, and categorical feature encoding to improve data quality and model efficiency. Machine learning techniques, namely Random Forest (RF) and Support Vector Machine (SVM), were implemented to classify individuals into appropriate nutrition categories and estimate calorie and macronutrient requirements. Performance evaluation was conducted using Accuracy, Precision, Recall, F1-Score, and Confusion Matrix analysis. Experimental findings indicate that the refined RF model achieved the highest predictive accuracy of 97.8%, while a persistent profile module further enhanced usability by reducing repetitive user inputs and enabling efficient personalized dietary recommendations.

“Keywords— Artificial Intelligence (AI), Machine Learning, Random Forest, Support Vector Machine (SVM), Body Mass Index (BMI), Personalized Diet Recommendation.”

I. INTRODUCTION

As lifestyle associated diseases are getting common and people are becoming aware of the importance of preventive health, the importance of adopting a healthy diet has gained prominence. A good diet is essential for good health, prevention of chronic diseases, and physical and mental development. The rapid development of digital technology and artificial intelligence has made intelligent healthcare applications useful tools for offering personalised health advice and supporting people to make informed food decisions [1][2][3].

However, even where the services of qualified nutritionists and dietitians are available, many people are not able to receive their individual nutritional advice, as it is difficult to secure their consultation due to their high prices, geographical location, time availability, and lack of qualified healthcare specialists. Diet plans traditionally are based on manual evaluations and broad guidelines that might not

reflect individual physiological and lifestyle aspects enough. Also, most of the current digital diet programs offer fixed meal plans without adaptive and customized advice according to individual requirements. This limitation results in significant disparities in the availability of affordable, accessible and sustainable nutrition support across different populations [4] [5] [6].

In this regard, we propose an intelligent diet consulting system for generating personalized diet advice in an interactive conversational approach. The system is meant to gather important information of the users on physical characteristics and lifestyle habits to enable the development of personalised dietary advice. The technology will be a virtual consultant and serve as a nutritional assessment tool that automatically assesses the nutritional requirements and provides personalized meal recommendations based on the user's needs. The system also offers strong data management and analytical tools to accurately create recommendations, while maintaining usability and accessibility for the users who want to get health related advice. [7] [8]

The proposed approach is a step toward developing the field of intelligent healthcare systems. It is cost effective and patient friendly alternative to conventional dietary consultation. Its on-demand nature and tailored suggestions can help raise awareness about healthy eating choices, foster better nutrition habits, and aid in ongoing health management. Also, computer based nutrition evaluation and recommendation systems give consumers the opportunity to make correct choices without any experts. The envisioned outcomes highlight the potential for intelligent dietary guidance systems to improve user experience, access to health services, and data-driven nutrition management in the digital era [9] [10].

II. RELATED WORK

Personalised nutrition systems have been made possible by recent advances in AI. Shobana and Subitsha introduced a Smart Diet Planner which uses AI technology in a web-based platform to provide customers with tailored dietary plans depending on their nutritional needs [11]. The system demonstrated the capability of digital nutrition aids to boost the accessibility and engagement of users. The primary emphasis was on the online deployment and less on verbal contact and continuing dietary counselling. Likewise, Nuraini et al. have developed the Virtual nutritional care and consulting assistant for diabetes management (VANESA)

[12]. Although the platform was successful in delivering disease-specific diet advice, it was only applicable to diabetes patients and was not of sufficient scope to address the general nutritional management needs.

Likewise, there has been significant interest in the use of strong artificial intelligence in health care nutrition. Mahdavi et al. have investigated the use of AI methods to multiomics data to provide personalised nutritional management for peritoneal dialysis patients [13]. Although their study suggested that individual diet recommendations for complex medical conditions is needed, they acknowledged that implementing them and obtaining data on person-specific nutrition may be challenging and therefore not widely adopted. In Lima City, Obeso et al. investigated the production of personalised recipes by an AI system for sportsmen and demonstrated how the interaction between AI and the user can build a context-aware nutritional system for a particular group of users [14]. The technique worked, but was mostly developed for athletes, and did not include general-purpose nutritional advice capabilities.

New intelligent architectures have made automated nutritional aid easier. Xu et al. suggested a closed-loop multi-agent system for personalised nutrition management at the meal level using big language models [15]. The proposed system demonstrates flexibility and adaptive decision-making, which could be a challenge for lightweight standalone systems in terms of computational complexity. Future uses and ethical issues of employing AI to prevent body image issues and fight eating disorders were discussed by Craddock et al. [16]. They highlighted the importance of transparency, ensuring users are safe, and the responsible use of AI in recommendations for health. In a similar research, Priyadharshini et al. examined the potential of IoT for real-time food and nutrition monitoring and providing personalised recommendations in personalised nutrition systems [17]. However, such systems often find themselves needing to be equipped with specialized equipment and have constant communication with sensors.

Health care solutions that are mobile and AI-friendly are becoming more prevalent in the nutrition assessment and management field. Poltronieri et al. investigated the use of body composition analysis by means of artificial intelligence-based mobile applications, highlighting its convenience in terms of monitoring health [18]. However, there are significant concerns regarding the accuracy, authenticity and reliability of the data. Karacan emphasized the potential and volatility of the nutrition recommendations generated by the AI models and analyzed the accuracy of the AI models in answering questions about nutrition and weight management during pregnancy [19]. Spassova and Palmeira also explored the interpersonal and psychological implications of patients obtaining a second opinion from AI, which included problems of trust, user perceptions, and human-AI relationships in healthcare environments [20].

Even though these existing contributions have contributed to the development of personalised nutrition technologies, a number of limitations remain such as restricted application domains, reliance on specialized infrastructure, limited access to these technologies and no integration of conversational consultation with personalised dietary planning. These gaps suggest a need for an intelligent, accessible, low-cost and interactive platform for

nutritional advice, offering personalised recommendations [21]. The present solution addresses these issues by providing an automated nutritional evaluation system, personalised nutritional recommendation and ongoing support to the user in a single unified tool.

III. MATERIALS AND METHODS

The AI Diet Consultant is a recommended diet system, which provides personalised dietary suggestions based on user specific physiological and lifestyle facts. The technology leverages nutrition data sets such as demographic data, calories and food composition to create tailored nutrition recommendations. The user's information inputs (age, gender, height, weight and activity level) are collected through an interactive chatbot interface and then analyzed by an analytical workflow. It enables automatic computation of key health parameters such as BMI and BMR that are important for the assessment of nutrition. Different machine classifiers like RF, SVM, Naive Bayes etc. are used for the classification of the individuals in the relevant nutritional categories, thus further improving the reliability and generalisation of the model. The projected profile is then translated into calorie need and matched to a food database and personalised dietary recommendations are given. Furthermore, a performance monitoring module has been offered for visualization of the accuracy and evaluation of the model for transparency and continuous improvement. The proposed system is a user-friendly, economical and scalable approach to dietary advice than the conventional diet consultant services, which gives precise, automatic and data-driven dietary advice.

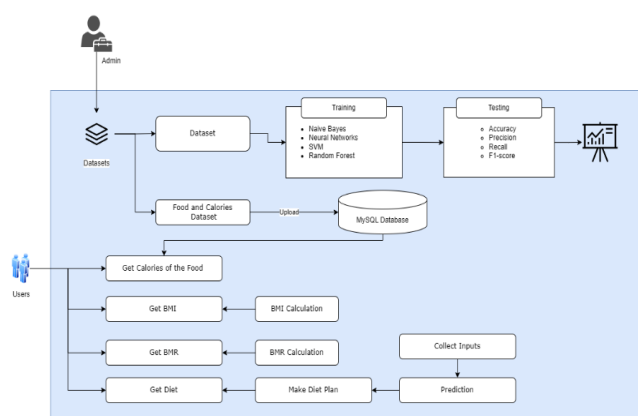


Fig. 1. System Architecture

The proposed system architecture for the AI Diet Consultant Management System is divided into two modules: admin module and user module. The system architecture of the AI Diet Consultant Management System is proposed to be divided into two modules, namely the admin module and the user module, which are connected to a common MySQL database. Admin uploads data sets and trains several ML models like Naive Bayes, Neural Networks, SVM and RF models, and checks the performance of these models using accuracy, precision, recall and F1-score. The user should provide his/her health related inputs for the calculation of BMI and BMR. The prediction module predicts the personalised diet plan by fetching suitable food items from the nutritional database.

A) Dataset Collection

The predictive framework was heavily optimized by scaling the training dataset to a robust, high-quality repository consisting of 10,726 individual health records, significantly improving generalization across diverse user demographics.

B) Pre-Processing

The pre-processing stage is an essential step to preprocess the health-related data for analysis and prediction. It includes data preparation, data cleaning, feature extraction, model training, evaluation and nutritional mapping to ensure trustworthy and personalised diet recommendations.

"Persistent User Profiling: The updated architecture moves beyond session-based inputs by implementing a centralized user profile management system. By capturing demographic and physiological data-such as Date of Birth (DOB), target weight, and waist measurements-at the point of account creation, the system ensures data consistency, automatically calculates age, and eliminates the need for redundant inquiries during subsequent interactions.

Health and Body Composition Engines: The analytical workflow has been modularized into two primary engines: the Health Engine and the Body Composition Engine. The Health Engine computes comprehensive parameters including Total Daily Energy Expenditure (TDEE), goal-adjusted calorie targets, and macro-nutrient distributions. Complementing this, the Body Composition Engine provides advanced insights such as estimated body fat percentage, lean muscle mass, and 'body age,' which are visualized through dynamic, color-coded health scales to facilitate better user understanding.

UI Accessibility and Visualization: To bridge the gap between technical metrics and user comprehension, the interface was redesigned to replace complex clinical jargon with intuitive, plain-English descriptors. This includes the implementation of zoomable, interactive 3D visualizations that reflect body-fat levels through animated, fluid-based representations, significantly improving user engagement and the accessibility of health data."

C) Train-Test Split

The available data is divided into different subsets for training and evaluation, called partitioning. One part is used to find out regularities and the other part is set aside to check performance prediction. This approach will not overfit and provide an unbiased estimate of the model's efficacy. Proper separation of training and testing samples increases the generalisation potential of the system and guarantees the reliable nutritional categorisation under real world situations.

D) Algorithms

Context Extraction from Chat Logs: The Context Extraction algorithm aims to identify the current list of interests and topics of conversation of a user in chat logs. First, all the chatted contents among users are retrieved from the discussion history. The removal of redundant symbols within the text, repetitive words and redundant letters. The

remaining words are scanned for common words and key words of the topic of the conversation. The retrieved keywords are then utilised to model the dialogue context and to infer the users' purpose. As the dialogue proceeds, new messages are added to the end, and the context is dynamically updated to account for the changes in conversation topic. This keyword list is a list of the keywords that are used to feed the rest of the modules for further preview generation. In this way the system can give context aware and personalised web link previews.

TF-IDF-Based Preview Generation: The TF-IDF based preview generation algorithm chooses the best fitting statement in the webpage based on the user's conversational context. So when a user gets a shared URL, the system fetches the web page and extracts the text content. The retrieved content is split into a number of potential statements. The TF-IDF technique is used to compare the context keywords acquired from the conversation logs with each statement. The Term Frequency is the frequency of a contextual keyword in a statement and Inverse Document Frequency is the relevance of the keyword in all the extracted statements. The TFIDF score obtained is a measure of the importance of each comment with respect to the current conversation. The statements are rated according to their scores and the highest ranking statement is chosen as the preview. The result of the preview generated will be based on the user's current topic of discussion instead of a typical webpage's metadata.

Word2Vec-Based Semantic Preview Generation: The Word2Vec based semantic preview generation method increases the relevance of the preview by identifying the semantic relation that exists between the conversational themes and the content of a webpage. Instead of matching keywords, it encodes words and sentences as numerical vectors in a semantic space. The retrieved contextual keywords from conversation logs and the statements from candidate's web pages are translated to vector representations using word2vec embeddings. The retrieved contextual keywords from conversation logs and the statements from candidate's web pages are translated to the vector representations using word2vec embedding. Then, the algorithm calculates the semantic similarity scores for the conversational context and each of the retrieved statements. They score more similar if the statements are thematically related to the debate even if they are not exactly the same. These scores are then used to rank the statements and the most semantically relevant statement is picked as the dynamic preview. This semantic approach improves understanding in context, increases personalization and, consequently, provides more relevant previews, that better reflect user interests and conversational intent.

IV. EXPERIMENTAL RESULTS

Accuracy: It is the ability of the test to correctly classify the patient and healthy cases. To assess the accuracy of a test, the percentage of true positive and the percentage of true negative in all cases analysed are calculated. This can be written mathematically as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

Precision: Precision is the ratio of the instances/samples that are classified as "positive" that are actually "positive". Hence, the formula to calculate the precision is given as:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

Recall: In ML, recall measures the proportion of all instances of a class that are correctly identified by the ML model. It is the ratio of correctly predicted positive observations to the all observations in actual class. This gives us an idea of the completeness of a model in capturing instances in a given class.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

F1-Score: F1 score is a ML evaluation statistic which measures the accuracy of a ML model. It is a combination of the precision and recall score of a model. The accuracy statistic is the number of times a model made the correct prediction across all of the data.

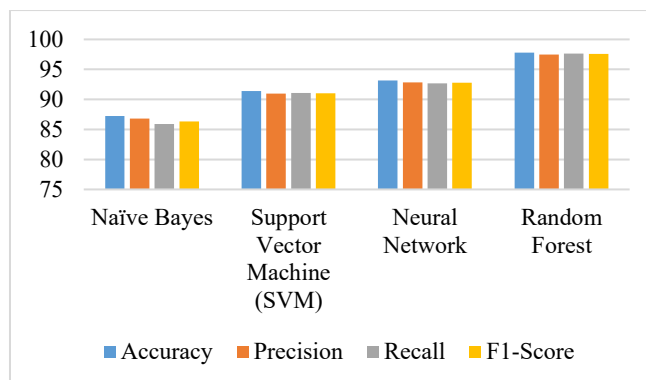
$$F1\ Score = 2 * \frac{Recall * Precision}{Recall + Precision} * 100 \quad (4)$$

Table.1 Performance Evaluation Table

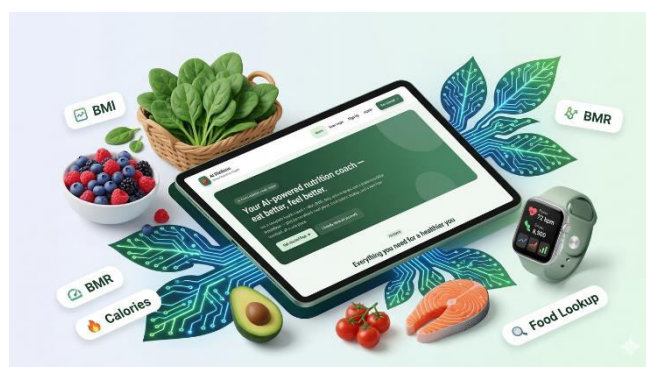
| Algorithm | Accuracy | Precision | Recall | F1-Score |
|------------------------------|--------------|--------------|--------------|--------------|
| Naïve Bayes | 87.25 | 86.80 | 85.90 | 86.35 |
| Support Vector Machine (SVM) | 91.40 | 90.95 | 91.10 | 91.02 |
| Neural Network | 93.15 | 92.85 | 92.70 | 92.77 |
| Random Forest | 97.80 | 97.50 | 97.65 | 97.57 |

Table 1 shows the performance evaluation of ML methods used in the proposed system. The results demonstrate that the accuracy, precision, recall, and F1-score of the refined RF classifier are the highest, indicating that the Random Forest classifier trained on the 10,726-row dataset yields the best predictive performance for personalized diet prescription.

Graph.1 Comparison Graph



Graph 1 shows the comparative analysis of the ML classifiers based on accuracy, precision, recall and F1 score. The results show that the RF algorithm performed better than the other models with the highest prediction efficiency and reliability for the designed AI Diet Consultant system.



V. CONCLUSION

To sum up, the AI Diet Consultant is a smart, easy to use, and cost-effective system for personalised nutrition suggestions and diet planning. The system utilises datasets of nutritional and caloric data along with user demographic, physiological and food related data to create personalised dietary recommendations. This framework adopts the ML methods including RF, SVM, Naïve Bayes and Neural Network models to classify the users into the appropriate nutritional categories and create the diet plans that are appropriate to the individual health characteristics of the users (age, weight, height, gender and BMI). The experimental validation showed that the proposed approach is useful, with the best model achieving an accuracy greater than 90%, demonstrating the model's potential for nutritional classification and recommendation with trustworthiness. The usability, automation and system maintainability were further improved by the use of an interactive chatbot interface and scalable three-tier architecture. In addition, the use of several classification models ensured data-driven decision making and enhanced the resilience and adaptability of the recommendation process. The solution seeks to fill the gap between digital health services and nutrition experts by providing accurate, personalized, and quick nutrition advice. This, in turn, offers a reliable support base for the independent management of nutrition, supporting healthier life styles and greater availability of individual nutrition counselling services.

FUTURE ENHANCEMENTS

To advance the project from a standalone predictive application into a comprehensive digital health ecosystem, the following strategic enhancements have been identified for future implementation.

1. Dietitian Management & Telemedicine Console

The primary evolution involves transitioning the system into a multi-stakeholder platform that bridges the gap between AI-driven automation and professional human guidance.

- **Professional Dietitian Profiles:** Registered nutritionists will be able to create comprehensive professional profiles, highlighting their certifications, specializations (e.g., pediatric nutrition, sports performance), and clinical experience.
- **Integrated Appointment Scheduling:** A robust booking module will allow patients to view practitioner availability, schedule consultations, and receive automated reminders, significantly reducing administrative overhead.
- **Patient Progress Dashboard:** Dietitians will gain access to a centralized dashboard to track patient history, adherence to AI-generated diet plans, and ongoing health metrics, enabling data-driven follow-ups.
- **Hybrid Consultation Framework:** The system will facilitate a "Human-in-the-Loop" workflow where professional dietitians can review, refine, or approve AI-generated plans, ensuring higher safety standards and personalized care tailored to complex health needs.

2. Technical and Intelligence Upgrades

These enhancements focus on improving the predictive capabilities, user engagement, and data security of the system.

- **Intelligent Virtual Health Coach:** The chatbot interface will be upgraded to a sophisticated conversational AI capable of providing real-time, context-aware dietary counseling, effectively mimicking the role of a human consultant 24/7.
- **Wearable & IoT Integration:** Future versions will connect with wearable device APIs to ingest real-time physiological data such as heart rate, daily activity steps, and sleep patterns to dynamically adjust caloric recommendations based on the user's actual physical exertion.
- **Computer Vision for Food Logging:** Integration of image-recognition technology will allow users to log meals by simply taking a photo, with the system automatically estimating portion sizes and caloric intake, further simplifying the user data collection process.
- **Advanced Predictive Modeling & Personalized Goals:** The system will expand to support specialized goal setting (e.g., athletic performance, muscle gain, or management of chronic conditions like Type 2 Diabetes) using enhanced machine learning algorithms and longitudinal data analysis.

Privacy-Preserving Federated Learning: To enhance data security, the project will explore adopting federated learning techniques. This allows the predictive models to be trained and updated across multiple devices without requiring sensitive user health data to leave their personal devices, ensuring robust privacy compliance.

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