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PERSONALIZED NUTRITION WITH AI: INVESTIGATE HOW AI CAN BE USED TO ANALYZE INDIVIDUALS' DIETARY HABITS, HEALTH DATA, AND GENETIC INFORMATION

1 Bhavishya Katta, 2 Venkata Chaitanya Kumar Suram, 3 Narsimha Chary Rajampetakasham, 4 Mounika Nalluri, 5 Chinna babu Mupparaju,

1 Senior System Analyst , Information Technology(Masters in Computer Science, Masters in Information System Security , Masters in IT), University of the Cumberlands , Austin, Texas, bhavishyakatta2@gmail.com

2 Senior Software Engineer, Information Technology(PhD in IT), University of the Cumberlands, Austin, Texas, Venkatsuram5@gmail.com

3 ETL Developer, Information Technology(PhD in IT), University of the Cumberlands, Beaumont, Texas , Rajampetakasham@gmail.com

4 Senior Software Engineer, Information Technology(Masters in Computer Information Systems), Murray State University, USA, mounikanalluri89@gmail.com

5 Software Engineer, Information Technology(Masters in Computer Science), University of Central Missouri, USA, chinnababumupparaju@gmail.com.

ABSTRACT

Clinical nutrition may soon see a dramatic shift due to the advent of artificial intelligence (AI), a cutting-edge medical technology. Complex data analysis, medical picture interpretation, and patient-specific dietary therapies can all benefit from AI's assistance. More and more people are looking to AI-powered software apps that can tailor their diet plans to their specific needs in order to encourage them to lead healthier lives. We provide a knowledge-based recommendation system that can deliver amazingly accurate diet plans to 10 separate user categories, including healthy persons and those with medical issues, by using an explicit dataset of expert-validated meals. A quantitative layer to combine meal ideas and a qualitative layer to ensure ingredients are compatible make up the suggested advisor's novel design. In the first level, you'll find an expert system that employs fuzzy inference based on an ontology of rules discovered by nutritionists. In the second layer, you'll find an optimization process that creates daily meal plans based on target and range nutritional values. We test the system extensively to see how successfully it recommends meal plans, how varied the meals are, and how appropriate the meals and meal plans are. A total of three thousand synthetic user profiles and weekly food plans were generated for the purpose of the evaluations.

1. INTRODUCTION

The term "artificial intelligence" was first proposed by American computer scientist John McCarthy (1927–2011) in 1955 when proposing a study to be carried out the following year at Dartmouth College in Hanover, New Hampshire. one, two.

Artificial intelligence (AI) is a branch of computer science that aspires to imitate cognitive processes, learning abilities, and knowledge management. It is finding more and more applications in both experimental and clinical medicine. The field of biomedical sciences and medicine has seen a proliferation of AI applications in the last several decades. Medical diagnostics, risk prediction, and treatment procedure support are three areas where artificial intelligence has fast expanding potential. The application of AI in diagnostics has yielded quantifiable clinical improvements, particularly in the fields of ophthalmology [3], radiology [4] and cardiology [5]. New medications were discovered with the help of AI [6]. New avenues for studying nutrition and medical sensing technologies have opened up thanks to AI advancement [7].

1.1. Artificial Neural Networks (ANNs)

An architecture similar to that of actual neurons in the human brain served as inspiration for ANNs, a popular modeling approach in artificial intelligence (AI) today. ANNs are mathematical models that use rows of processing units termed artificial neurons, coupled by artificial synapses, to process and calculate incoming signals. An ANN is constructed using three different kinds of layers. The input layer takes in raw data and passes it on to the hidden layer. In this second level, learning really takes place. The output layer is responsible for collecting analysis results and generating output data. It is possible for a neural network to have hundreds of individual units. Weights are modifiable parameters of an ANN, making it a parameterized system. Large training sets are required for ANNs because these parameters need to be estimated. Artificial neural networks (ANNs) learn not from code but from experience, by seeing patterns and correlations in data.

When dealing with datasets that have non-linear dependencies, an ANN really shines. Data used to solve biological problems can come from a variety of sources, including books and experiments. A model for experimental decision-making algorithms that makes use of ANNs and has been created during the past 20 years assesses the results of biochemical tests when given clinical data and reference values [8]. Using mass spectrometric fingerprints of whole mammalian cells, this approach was also used to assess levels of cross-contamination in cell cultures [9]. Drug analysis is one area where ANNs have shown to be quite helpful [10]. One intriguing use of ANNs is in making predictions about the connection between the Mediterranean diet, health outcomes, and cognitive abilities [11]. Because of its obviously non-linear properties, body composition assessments have demonstrated the utility of ANNs [12]. Clinical dietetics stands to gain a great deal by applying ANN modeling.

It should be mentioned that neural networks can be integrated with fuzzy logic methodology (FLM). Improving precision, dimensionality, and structural simplicity are the goals of this branch of artificial intelligence. Converting models based on FLM into neural networks and creating fuzzy neural networks are both within the realm of possibility.

2. MACHINE LEARNING (ML)

Machine learning (ML) is an AI subfield that focuses on automated algorithmic learning. Mathematical models for decision-making could be created by ML algorithms. These models are built automatically from big datasets of training data. In the latter decade of the 1900s, ML techniques became widely used in search engine applications. With the application of ever-improving ML algorithms, the area of organic synthesis was expected to make great strides in the decades that followed [13]. The biomedical sciences and clinical medicine benefit greatly from this branch of artificial intelligence, even though these expectations have not been entirely satisfied. Machine learning risk models, both supervised and unsupervised, can be trained using clinical datasets [14]. Improvements in patient data analysis are possible as a result [15].

Personalized medicine, biomedical research, and computer-assisted diagnostics are all fields that could benefit from ML in the future, according to some [16]. Researchers studying diabetes are increasingly turning to machine learning methods, especially for tasks like blood glucose level prediction and the development of closed-loop systems that simulate the human pancreas [17]. Research on the gut microbiota could benefit from ML algorithms, according to the massive datasets collected in these studies [18]. The glycemic response to physical activity may be accurately predicted by an ML algorithm that takes into account the baseline microbial fingerprints of the gut microbiota, as demonstrated in a recent work by Liu et al.

One kind of ML is deep learning (DL). This branch of artificial intelligence has seen widespread use in fields such as speech and picture recognition, as well as translation from one language to another. Medical diagnostics is another major area where DL finds utility. Autonomy of the algorithm in constructing sets of features used for recognition is a key aspect of DL that distinguishes it from supervised ML.

3. PRINCIPLES OF ARTIFICIAL INTELLIGENCE

Machine learning (ML), deep learning (DL), and natural language processing (NLP) are the three most common AI methodologies, as seen in Figure 1.

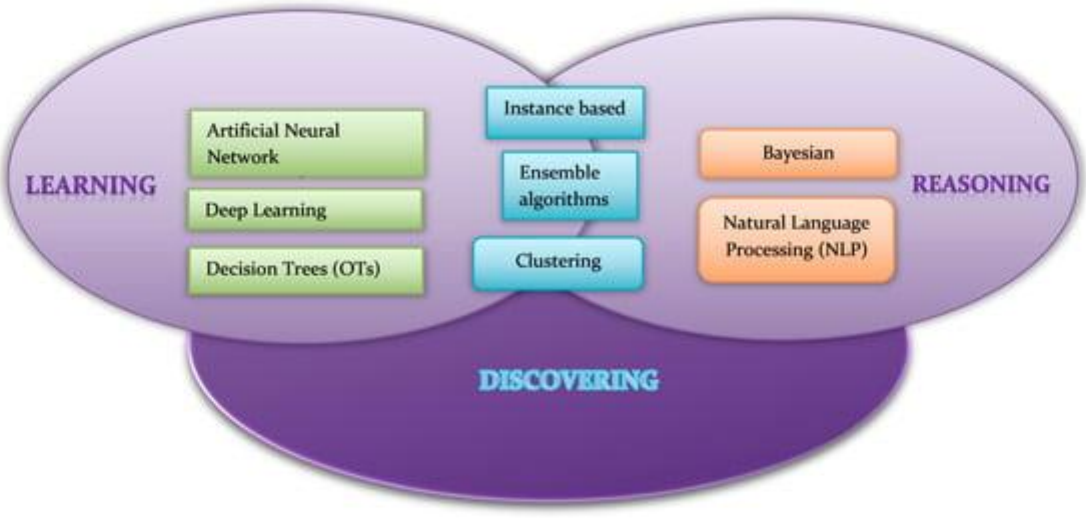


Figure 1. A schematic representation of the most commonly known AI methods.

Several similarities exist between the classic statistical technique and ML, a subset of AI. It encompasses both supervised and unsupervised learning, can tell the difference between accurate and inaccurate classifications, and is prediction-oriented thanks to variable algorithms. In order to enhance predictions, particularly in classification or regression, supervised learning employs techniques like k-nearest neighbor (KNN), support vector machines (SVMs), decision trees (DT), and random forests (RF). Without the use of labels, unsupervised learning algorithms search for inherent or latent relationships in the data (particularly for purposes of grouping, extraction, and visualization).[19-22]

When applied to data on food consumption, macronutrient patterns, and eating habits, ML algorithms like as RF, SVM, and KNN shine. Predicting undernutrition in children younger than five and determining the risk variables for overweight and obesity in infants born prematurely are two examples of ML's practical applications. Using standardized statistical models, KNN and RF algorithms can determine long-term cardiometabolic risk based on food patterns. The risk of cardiovascular mortality can also be better predicted with the help of RF algorithms.

However, DL—a branch of ML concerned with the development of self-learning systems—uses a neural network of algorithms rather than structured data and does not require external categorization. The system determines whether the classifications require modification and finds the unique data features. Furthermore, DL needs over a million pieces of data (e.g., texts, photographs, social media) to provide good results, in contrast to ML, which uses a manageable database and is employed for basic, repetitive jobs. This is why its applications are more intricate and underutilized.

Lastly, natural language processing (NLP) is widely utilized in text analysis, translation, and voice recognition. It has the ability to paraphrase, answer queries, and discover context and meaning. NLP finds particular use in medical file analysis, blog analysis, and social media data collection and organization.

4. APPLICATIONS OF AI IN NUTRITION

Diet and gut microbiota

The utilization of AI approaches could potentially be employed to conduct the investigation of the relationships between nutrients and gut bacteria. It is worth mentioning that studying various probiotic effects can lead to the creation of more effective probiotics, combinations of probiotics, or even synthetic probiotics using synthetic biology methods. In addition, a number of refined personalized models have been created, including the "enbiosis model" that is thought to be sufficiently effective in creating customized food plans to enhance microbiome. [23-25] This AI-assisted eating plan significantly reduced irritable bowel syndrome symptoms in a pilot clinical trial when compared to a control diet. Using AI-powered algorithms, which include gut microbes, significantly improved cardiovascular risk prediction models.

4.1 Nutrigenomics and personalized nutrition

Bioinformatics' application of AI has yielded practical methods and tools for the collection, organization, and analysis of massive biological datasets including genetic, nutritional, and related ones. After then, these datasets can be integrated and analyzed by AI algorithms to find valuable patterns and correlations. For more precise results or personalized forecasts, AI can be used to construct prediction models with biological data. Algorithms powered by artificial intelligence can, for instance, tailor nutritional suggestions to each person's unique genetic profile by combining genomic data with nutrition databases. [26] Artificial intelligence can also suggest individualized dietary treatments by considering genetic variants linked to food metabolism. Bioinformatics and AI can work together to produce individualized nutrition plans by combining genomic data, nutritional assessments, lifestyle factors, and health records.

4.2 Personalized nutrition

Customized eating regimens can be more easily created with the use of AI. Different biochemical, metabolic, genetic, and gut bacterial components may account for varied phenotypic responses to particular treatments; this is an implication of a tailored strategy. Bioinformatics and AI have the potential to discover biomarkers linked to particular dietary treatments or health results. A deeper comprehension of the molecular pathways underlying nutrition-related disorders and the development of targeted therapies are both facilitated by the aforementioned. Incorporating the computational power of bioinformatics with the complex algorithms and learning capabilities of AI allows researchers to enhance our comprehension of nutrition-related phenomena, develop personalized therapies, and provide evidence-based recommendations to maximize human health and wellbeing. An example of a personalized nutrition database is Nutri-Educ, which may be used by algorithms to drive dietary adjustments.

4.3 Food composition

Food safety, product creation, and overall nutrition are all greatly impacted by the ability to accurately forecast food components. Typical approaches to food composition analysis are labor-intensive, costly, and necessitate a large amount of laboratory testing. But new AI developments provide a great chance to get beyond these limits and make accurate and efficient food component forecasts. A recent study found that ANNs accurately predicted the chemical makeup of peach fruit, suggesting that AI can be effectively and practically used in the food industry. [27-29]These findings are consistent with the fact that, as compared to response surface approach, ANN predicts the garlic's phenolic and flavonoid content more accurately. ANN is also useful for determining the rheological and physicochemical properties of several foods, including tomatoes, honey, and cow's milk.

4.4 Dietary assessment with the use of food images recognition techniques

There are a number of research and individual level difficulties associated with dietary assessment. Principal component analysis is one of several developed methods for analyzing food and meal patterns; nevertheless, all of these methods depend on participants reporting their own information. As the size of food databases keeps growing, there is a growing need for innovative methods like food image recognition that make use of deep learning techniques. For instance, the "NutriNet" program was developed and rigorously tested on over 225,000 photos of 520 different foods and drinks; the

GoCARB app, on the other hand, was just as well as dietitians in estimating carbs. [30-33] With just the use of smartphone images, the goFOODTM software could calculate roughly how many calories and macronutrients were in a certain meal. As a result, nutritional evaluation in human research may be enhanced by these new technologies.

5. METHODOLOGY

The suggested nutritional advisor can analyze user characteristics and then provide NPs (nutritional plans) for the day. To be more precise, the adviser is made up of two parts: that portion of the system that generates NPs and the RDSS. According to research [41], the RDSS figures out what the user needs by looking at their profile, the available meals, and an ontology of qualitative rules collected from nutrition experts. In order to provide daily meal plans, the NP generating component mixes the right meals. With this kind of decoupled architecture, we can evaluate the recommended meal plans for the suitability of the meals and the meal plans themselves, and for the variety of meals in each plan, independently. This gives us a better idea of how accurate the system is when making recommendations. Figure 1 shows these components and their interplay; further explanation is provided below.

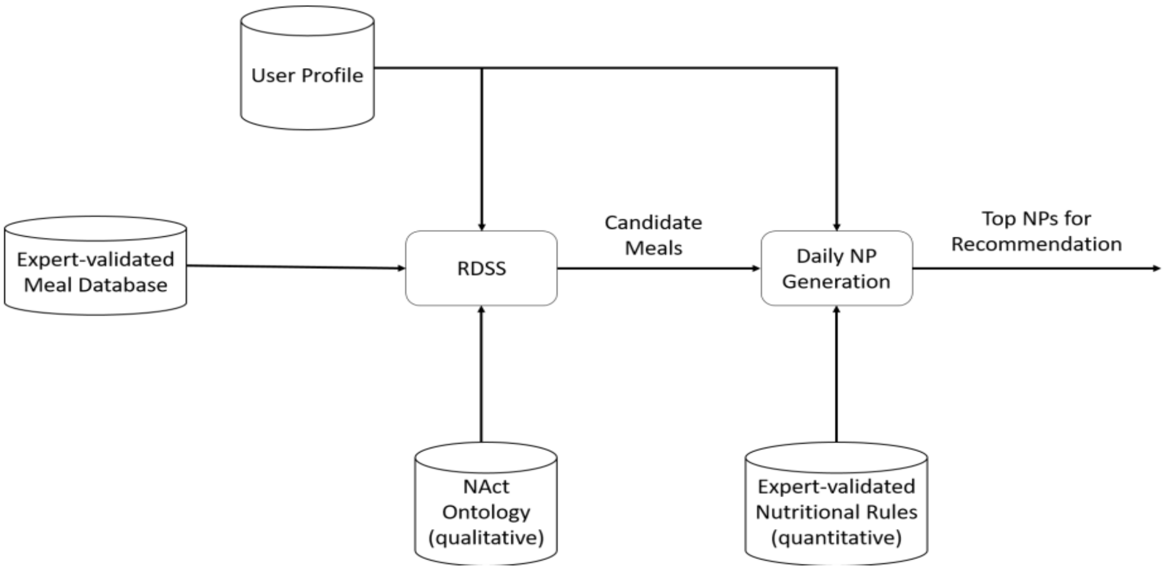


Figure 1. Architecture of the AI-based nutritional advisor

5.1 Supported User Groups and User Profile Modelling

From healthy teenagers and adults to those with a variety of medical issues and athletes, our system caters to ten distinct user categories (Table 1). We can further classify these user groups into three broad divisions:

A. Those in good health who shouldn't be expected to need the assistance of a medical professional.
B. People that would be assumed to require nutrition specialist monitoring.
C. People whose health is such that they should be closely monitored by dietitians and doctors.

Dietitians and doctors worked together on the PROTEIN project to create unique user profiles for each of the three supergroups. A user's profile includes a number of variables that reflect their appearance, eating habits, health status, personal preferences, and other relevant information, along with their associated reference ranges, priority, and other properties. In this experimental investigation, we employ a single profile model for all user categories to keep things simple. Dietary calculations require the user's sex, age, and other important physical characteristics; the unified user profile model also records the user's dietary preferences (such as vegan or halal) and health issues (such as intolerances, deficiencies, allergies, or medical conditions).

5.2 NAct Ontology

A goal of the PROTEIN project was to model evidence-based expert knowledge through the development of an ontology. For every potential change to a person's diet, earlier AI expert systems recommended changing one aspect of that person's lifestyle. However, using semantic entities and rules, PROTEIN's knowledge-based expert system technique takes a more comprehensive approach, with the ontology serving as its foundation. This allowed us to establish a connection between the subject's current circumstances, standardized European nutritional and wellness standards, and the implicit and explicit dietary and wellness goals of all users.

The seven steps of the Methontology methodology—specification, knowledge acquisition, conceptualization, integration, implementation, evaluation, and documentation—formed the basis for the construction of NAct ontology. The technical team (ontology engineers) and health and nutrition specialists worked closely together and co-created each stage of the ontology's lifetime, with the exception of specification, which was established in great detail early on.

6. RESULTS AND DISCUSSION

Table 1. Evaluation (top-n accuracy) of meal promotions by the RDSS.

	Accuracy			
Deficiency/Goal to Increase	**Top-20**	**Top-10**	**Top-5**	**Top-3**
Protein	1.000	1.000	1.000	1.000
Fat	0.800	0.800	1.000	1.000
Carbohydrates	0.750	0.800	0.800	1.000
Iron	1.000	1.000	1.000	1.000
Average	**0.8875**	**0.900**	**0.9500**	**1.000**

Therefore, it was crucial to determine if the advertised meals really had the highest concentration of the nutrient in question. The evaluation was conducted for four distinct n-values, and the outcomes are displayed in Table 1.

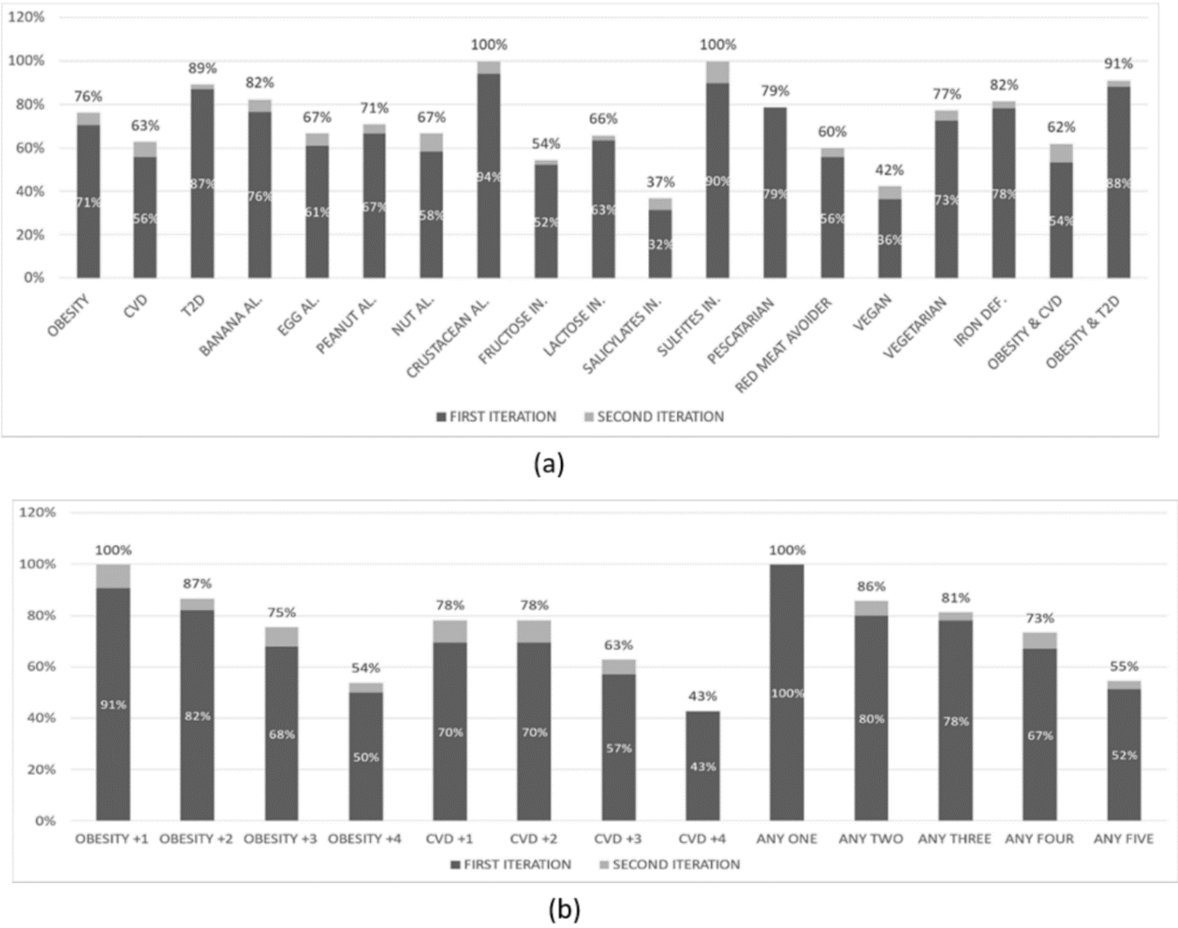
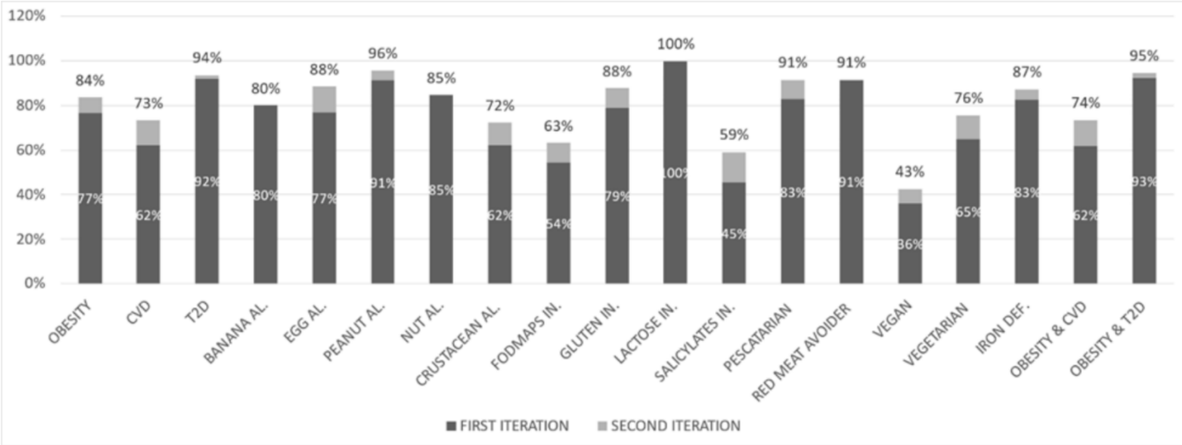
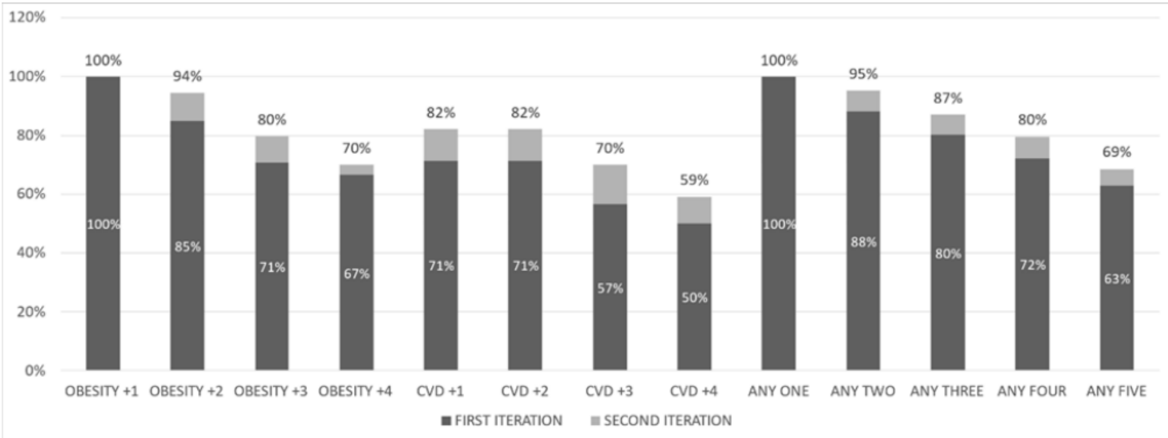


Figure 3. NP generation rate for simulated user profiles when (a) all of the conditions are met, and (b) all of the conditions are met (first experiment).

Figure 3 below displays the outcomes of the initial experiment. In the first cycle of this experiment, the total NP production rate was 70%; in the second cycle, it increased to 75%.



(a)



(b)

Figure 4. Calculation of the rate of NP formation for virtual user profiles that meet (a) at least one of the conditions given and (b) all of the conditions mentioned (second experiment).

See Figure 4 below for the second experiment's results. In the first cycle of this experiment, the total NP formation rate was 76%; in the second cycle, it increased to 83%.

Table 2. Recommendation accuracy of the generated daily meal plans in terms of macronutrients and other dietary components.

User Group	Macronutrients Accuracy (%)	Other Dietary Components Accuracy (%)
Healthy adolescents	99.32	89.24
Healthy adults	99.75	97.65
Healthy older adults	99.78	95.09
Adults with excess weight	93.84	94.10
Athletes	82.11	31.07
Adults with obesity	98.66	N/A
Adults with CVD	81.36	N/A
Adults with T2D	97.58	97.24
Adults with iron deficiency	95.55	75.53
Adults with a diet low in fruits and vegetables	99.62	99.66
Overall accuracy	**92.65**	**85.86**

According to Table 2, the daily meal plans provided by the proposed AI-based nutritional advisor were accurate for all user groups when it came to macronutrients and other dietary components. Since the nutritional experts did not lay out any mandatory or recommended guidelines for adults who are overweight about other aspects of their diet, the prospective nutritional counselor is allowed to set its own standards. An empty string ("N/A") is assigned to this since it does not involve target values.

CONCLUSIONS

In this study, we present a recommendation framework that employs a two-stage architecture for diet modeling to develop an appropriate and safe meal plan recommender system. In this case, the PROTEIN AI Advisor accomplishes three goals by incorporating the evidence-based recommendations of nutritionists and global regulatory agencies: (i) avoid ingredients that could be harmful; (ii) create daily meal plans for different populations using quantitative rules; and (iii) compile a database of meals that have been validated by experts. In this study, we break down the recommendation process into its component elements and assess the system's capacity to manage and respond to "complex" user profiles, meal plans offered, and user-specific meal recommendations. All user groups were able to benefit from the system's precise macronutrient and other dietary component recommendations in their daily meal plans (92.65% and 85.86%, respectively). But the amount of meals in the database that the recommender system could use was a constraint on how accurate it could be.

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