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DEVELOPING MENU PLANNING SOFTWARE USING OPTIMIZATION AND ARTIFICIAL INTELLIGENCE ALGORITHM

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ABSTRACT
In today's world, awareness of health and nutrition is growing, emphasizing the need for personalized nutrition recommendations and reducing food waste. This study collected demographic data and food preferences from users and analyzed them using artificial intelligence models. A model developed with the Random Forest algorithm was trained to predict users' future preferences and guide menu planning. Tests showed that combining AI with optimization techniques successfully creates user-focused menus, enhancing satisfaction and reducing food waste. The study also highlighted challenges related to the dataset's size, pointing to a need for more qualitative data. The developed model provides innovative solutions for catering companies and institutions offering mass dining, improving employee satisfaction while minimizing waste. Future research aims to refine the model for broader applications.
Keywords: Artificial intelligence, optimization algorithms, linear programming, personalized menu, catering

OPTİMİZASYON VE YAPAY ZEKÂ ALGORİTMALARI KULLANARAK MENÜ PLANLAMA YAZILIMI GELİŞTİRİLMESİ

ÖZ
Günümüzde sağlık ve beslenme bilinci giderek artmakta, bu da kişiye özel beslenme önerilerinin ve gıda israfının azaltılmasının önemini vurgulamaktadır. Bu çalışmada, kullanıcılardan demografik veriler ve gıda tercihleri toplanarak yapay zeka modelleri ile analiz edilmiştir. Random Forest algoritması kullanılarak geliştirilen bir model, kullanıcıların gelecekteki tercihlerini tahmin etmek ve menü planlamasına rehberlik etmek üzere eğitilmiştir. Yapılan testler, yapay zeka ve optimizasyon tekniklerinin birleştirilmesinin kullanıcı odaklı menüler oluşturduğunu, memnuniyeti artırdığını ve gıda israfını azalttığını göstermiştir. Çalışma ayrıca, veri setinin boyutuyla ilgili zorluklara dikkat çekerek, daha nitelikli verilere olan ihtiyacı ortaya koymuştur. Geliştirilen model, toplu yemek hizmeti sunan catering şirketleri ve diğer kurumlar için yenilikçi çözümler sunarak çalışan memnuniyetini artırırken israfı da minimize etmektedir. Gelecek araştırmalar, modelin daha geniş uygulamalar için geliştirilmesini hedeflemektedir.
Anahtar kelimeler: Yapay zekâ, optimizasyon algoritmaları, doğrusal programlama, kişiselleştirilmiş menü, catering

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INTRODUCTION

In today's health-conscious era, personalized nutrition is becoming crucial. This research aims to use artificial intelligence (AI) and optimization algorithms to develop tailored menu plans based on personal health and dietary preferences. General nutrition guidelines often fall short of meeting individual needs; this project targets creating scientifically grounded, customized diet plans that align with each person's unique requirements. Technological advancements are pivotal in enhancing life quality by providing personalized health and nutrition solutions. AI and optimization algorithms are particularly effective in formulating diet plans that cater to specific health statuses and dietary choices. This integration of technology not only caters to personal preferences but also enhances nutritional effectiveness and employee satisfaction in organizational settings, particularly in catering services that often overlook individual dietary needs, leading to increased food waste and reduced satisfaction (Hou et al., 2022). The goal of this research is to optimize how catering companies address the nutritional demands of their clientele, minimizing waste and enhancing meal satisfaction. When dietary preferences are ignored, not only does food waste escalate, but it also leads to financial and environmental drawbacks. By applying AI and optimization techniques, the developed model efficiently generates meal plans that reduce waste and are attuned to the diverse preferences of employees. This model is not only a solution for catering companies but is also applicable to broader mass nutrition services, promoting more sustainable and efficient food service operations. In summary, this study illustrates the feasibility of creating personalized menu plans with AI and optimization, aiming to boost employee satisfaction and minimize food waste. The model has demonstrated effectiveness and promises broader application in future enhancements across various sectors.

Artificial intelligence and machine learning are increasingly integrated into the food industry, revolutionizing various aspects of food processing, manufacturing, logistics, and supply chain management. Known as Industry 4.0 or the Smart Factory, this modern era utilizes AI to improve efficiency, minimize waste, and ensure food safety. With food safety regulations being a primary concern, transparency in the food supply chain is crucial. AI supports monitoring the entire supply chain process, aiding in price prediction, production process optimization, inventory management, and logistics management. AI can even determine the origin of a specific crop. Tools like Symphony Retail-AI help predict demand for transportation, pricing, and inventory, preventing overstock and waste (Hebbar, 2020). Previously, manufacturers needed numerous employees for repetitive tasks such as food sorting. AI-based applications can now easily identify which potatoes are best for chips and which are ideal for French fries, making the sorting process faster, more efficient, and accurate (Misra et al., 2022). Producing various items involves complex systems. Machine learning plays a vital role in the predictive maintenance of these large machines, reducing operational costs and labor, optimizing resource use, and increasing output. It employs machine learning techniques, cameras, sensors, and internet connectivity (Sharma et al., 2021). Machine learning is also crucial in food delivery, facilitating smart logistics and tracking crops and vegetables. It reduces vegetable waste and enhances restaurant meal delivery (Li et al., 2019). Modern industrial and logistical systems benefit from expansive and powerful computing networks. Sensors, machines, systems, intelligent devices, and people within these networks generate constant data. With increased computing power, this Big Data is processed more quickly and in greater detail than ever before. These advancements have ushered in Industry 4.0 or the Smart Factory, highlighting the significance of artificial intelligence technology (Ahmed and Kim, 2017).

THEORETICAL BACKGROUND

Optimization and linear programming

Optimization is a mathematical process used to adjust given parameters to best achieve an objective or goal function under specific constraints. The primary aim of optimization is to find the most suitable solution for a given problem, and it is applied in various fields such as engineering, finance, logistics, and AI (Precup et al., 2020). This process is typically used in situations where costs, time, or distance need to be minimized, or where revenue, efficiency, or performance need to be maximized (Gong, 2022).

Linear Programming (LP) is one of the most common forms of optimization problems. LP determines decision variables under linear constraints to optimize an objective function. The LP gained significant momentum with the development of the simplex method by George Dantzig in 1947 (Chandru and Rao, 1998). The simplex method provides time-efficient solutions to LP problems and has been widely applied, from military logistics to commercial applications (Dantzig, 1982).

The applications of LP are quite diverse. It is widely used in industrial and scientific research for cost-benefit analyses, optimizing agricultural yields, planning routes in commercial aviation, and many other areas (Kulhari, 2023). The flexibility of LP stems from its ability to represent various constraints and objectives through linear equations and inequalities. Additionally, LP problems can be solved using various algorithms, such as the simplex method, primal-dual method, and interior-point method (Tiwari and Agrawal, 2022).

However, many real-world problems are not limited to continuous variables. Some problems require decision variables to take integer values, especially when the nature of the decisions is discrete. In such cases, a more complex method known as Mixed Integer Linear Programming (MILP) comes into play.

Optimization and linear programming

MILP is a more complex form of LP that involves both continuous and integer variables to solve optimization problems. MILP aims to maximize or minimize an objective function under linear constraints (Miltenberger, 2023). This approach is suitable for modeling scenarios where both discrete (integer) and continuous decision variables coexist. For example, in a logistics problem, optimizing both the number of vehicles (integer) and the quantity of goods to be transported (continuous) simultaneously.

MILP shares similarities with LP as both seek to optimize an objective function under specific linear constraints. However, the key difference lies in the inclusion of integer constraints in MILP models, significantly altering the solution strategies. While LP models deal solely with continuous variables, MILP models incorporate integer variables, allowing for more realistic decision-making scenarios.

MILP problems typically fall into the NP-hard category, meaning they are considerably more challenging to solve compared to LP problems. Common methods for solving MILP problems include Branch-and-Bound, Branch-and-Cut, and Cutting Plane techniques. These methods are designed to systematically explore the solution space and effectively narrow down potential solution candidates.

Branch-and-cut method

The Branch-and-Cut method is a widely used and highly effective technique for solving MILP problems. This method combines two fundamental approaches: Branch-and-Bound and Cutting Planes.

Branch-and-Bound: This approach involves partitioning the solution space into smaller subproblems (branching) and working on each subproblem individually to reach an optimal solution. In each branch, solutions that violate integer constraints are excluded. This method helps manage the complexity by breaking down the problem into more manageable parts and solving each part separately.

Cutting Planes: This technique adds cutting planes to the solution space to exclude fractional solutions and narrow the feasible region. Cutting planes are mathematical constraints that eliminate portions of the solution space that do not contain integer solutions. Common methods include Gomory cuts and capacitated cuts.

The Branch-and-Cut method is particularly effective for solving MILP problems. Initially, a linear relaxation of the problem is solved, ignoring the integer constraints. The solution obtained usually contains fractional values. At this point, cutting planes are added to narrow the solution space and enforce integer solutions (Balcan et al., 2022). If the linear relaxation solution does not contain integer values, the solution space is partitioned (branching) into subproblems, and each subproblem is solved individually. This process is repeated until the optimal solution is found, adding new cutting planes at each iteration to enforce integer constraints (Basu et al., 2023).

MILP and the Branch-and-Cut method find extensive applications in logistics, production planning, supply chain management, and many other fields. These methods provide effective solutions for complex and large-scale optimization problems, offering significant advantages in decision-making processes.

Artificial intelligence and random forest algorithm

AI is a multidisciplinary field of computer science aimed at creating intelligent machines capable of performing tasks that typically require human intelligence. These tasks include reasoning, learning, problem-solving, perception, and language understanding. AI integrates concepts and methodologies from various domains such as mathematics, statistics, computer science, neuroscience, and cognitive science (Russell and Norvig, 2003). One of the key subfields of AI that focuses on how these intelligent capabilities are acquired and utilized is Machine Learning.

Machine Learning (ML) is a subset of AI that focuses on the development of algorithms that enable computers to learn from and make decisions based on data. Unlike traditional programming, where specific instructions are coded, ML algorithms build models based on sample data, known as training data, to make predictions or decisions without being explicitly programmed for the task (Nasteski, 2017). One of the most common approaches within machine learning is Supervised Learning, where algorithms are trained on labeled datasets.

Supervised learning is a type of machine learning where the algorithm is trained on labeled data. This means that each training example is paired with an output label. The goal of the algorithm is to learn a mapping from inputs to outputs so that it can predict the output for new, unseen data accurately.

Supervised learning tasks can be divided into two main categories: classification and regression. In classification, the goal is to predict discrete labels, such as determining whether an email is spam or not. In regression, the goal is to predict continuous values, such as forecasting house prices based on historical data.

Common algorithms used in supervised learning include decision trees, support vector machines (SVM), k-nearest neighbour (KNN), Naive Bayes, artificial neural networks, and random forest algorithms.

In this study, classification algorithms were utilized to predict user preferences and create personalized menu recommendations. Classification algorithms are particularly effective when the data needs to be divided into distinct categories. The data used in this study includes user preferences and eating habits, serving as a labeled dataset for the model to predict future preferences. Among the classification algorithms tested, the Random Forest algorithm was chosen for its robustness and performance.

The Random Forest algorithm is an ensemble learning method used for classification and regression tasks. Developed by Leo Breiman and Adele Cutler, it operates by constructing multiple decision trees during training and outputting the mode of the classes (classification) or mean prediction (regression) of the individual trees (Breiman, 2001). The Random Forest algorithm is preferred for its multi-class capabilities and its ability to reduce overfitting. By aggregating the results of multiple decision trees, it provides higher accuracy and compensates for the errors of individual trees. Additionally, the algorithm helps in determining which features are most influential in making predictions and generally performs well across different datasets and problems.

The Random Forest algorithm works based on two key principles: bagging (bootstrap aggregating) and random feature selection. Bagging involves creating multiple subsets of the original dataset with replacement and training a separate decision tree on each subset. This increases the model's ability to generalize and reduces the risk of overfitting. Random feature selection means that at each split in the decision trees, a random subset of features is chosen, ensuring the trees are diverse and further reducing the risk of overfitting. It performs well on large datasets and high-dimensional spaces, making it applicable in fields such as healthcare, finance, marketing, and bioinformatics.

For the task of accurately predicting users' food preferences and providing personalized menu recommendations, the Random Forest algorithm was found to be particularly effective. It outperformed other tested algorithms in terms of accuracy and overfitting reduction, establishing itself as a reliable and efficient method for classification problems (Liaw and Wiener, 2002).

MATERIAL AND METHOD

This study aims to develop software using optimization and AI algorithms that catering companies can use to create personalized menus for their clients. The software provides balanced menu recommendations based on employees' personal data and dietary preferences, aiming to meet their health and nutrition goals while increasing employee satisfaction and reducing food waste. The flow diagram of the method used is shown in Figure 1. This section provides a detailed description of the methods and techniques used.

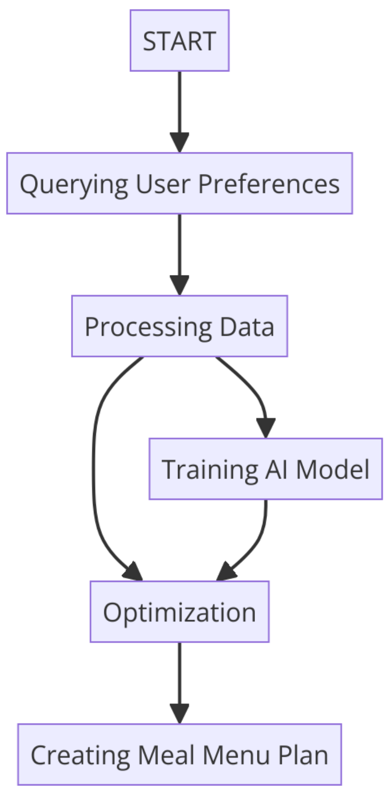

Figure 1. Flow diagram.

Tools and technologies used

This project aimed to develop software that can be utilized by catering companies. The development process involved creating a website that utilizes REST API services to manage optimization and AI functions. These REST APIs were essential for integrating optimization and AI functionalities into the web application. Various libraries and frameworks were employed in the development of this application. The website was designed using modern web development frameworks to ensure a user-friendly interface where users could input their food preferences. This interface then communicated with backend services via REST APIs.

To manage optimization tasks, the PuLP library was used. PuLP is a Python library for linear programming, which played a crucial role in solving the optimization problems involved in menu planning. The Random Forest algorithm was also implemented using the Scikit-learn library to predict user preferences based on their input data. Pandas' library was used for data manipulation and analysis, facilitating the efficient handling of large datasets. The Joblib library was utilized to serialize the trained machine learning models, ensuring that the models could be saved and loaded efficiently without retraining. Overall, the development of this menu planning software for catering companies involved the use of web technologies, REST APIs, and various Python libraries such as PuLP, Pandas, Scikit-learn, and Joblib.

Data collection and preprocessing

The datasets utilized in this project comprised user preferences and nutritional information. User data was collected through surveys that captured demographic details and food preferences. This data was then labeled to effectively train the machine learning models. Additionally, nutritional datasets, which included detailed nutritional information for various food items, were sourced from the Nutrition Information System. These datasets were essential for accurately predicting user preferences and optimizing menu planning to meet dietary requirements and health standards.

The data collection process involved conducting a series of surveys targeted at employees of companies partnered with catering firms. The survey included questions about demographic information such as age, gender, marital status, and activity level, as well as detailed questions regarding food preferences. The survey comprised approximately 20 questions, with food-related questions offering five different response options: "Never," "Rarely," "Moderately," "Often," and "Very Often."

Since this project did not collaborate with a real catering company, the data used was synthetically generated for experimental purposes. This synthetic data generation was performed using Python and various libraries. Specifically, the random library was utilized to adjust the probabilities of survey responses, allowing the creation of datasets under different scenarios. This approach enhanced the project's flexibility and the ability to conduct extensive testing.

Survey results were converted into numerical format for data processing and analysis. This transformation enabled the data to be processed by machine learning algorithms and optimization models. The numerical conversion was carried out using the One-Hot Encoding function, which converted each survey response into corresponding numerical values. Finally, the processed numerical data was stored in a database, making it accessible via API for various analyses.

Constraints

In the optimization model, constraints are based on various nutritional values and user preferences. These constraints are set to meet users' daily needs for calories, protein, carbohydrates, and fats. These general constraints ensure that the model meets the users' requirements for a healthy and balanced diet.

Integration

Developed using Python and the PuLP library, the model employs the CBC_CMD solver, which utilizes the Branch-and-Cut algorithm to effectively solve complex MILP problems. The

AI model was trained to predict users' meal preferences by analyzing collected data using the Random Forest algorithm. The AI model's predictions were then integrated into the optimization process to generate meal plans.

Table 1. Survey Questions

1	What is your age?
2	What is your gender?
3	What is your activity level?
4	What is your marital status?
5	How often do you prefer meatballs?
6	How often do you include kebab or stew dishes in your meal preferences?
7	How often do you consume fried meat dishes?
8	How often do you prefer chicken dishes?
9	How often do you eat fish dishes?
10	How often do you prefer vegetable dishes?
11	How often do you consume olive oil-based dishes?
12	How often do you eat meat and vegetable dishes?
13	How often do you have soups?
14	How often do you consume rice?
15	How often do you eat pastries?
16	How often do you prefer pasta and noodles?
17	How often do you prefer salads and cold dishes?
18	How often do you consume desserts?
19	What is your daily beverage consumption like?
20	How often do you consume fruit?

Table 2. Constraints

1. Four Types of Dishes:
- Each menu must include four different types of dishes, categorized into four groups, with one dish from each category.
2. Specific Order of Serving:
- The dishes in each menu must be served in a specific order.
3. Unique Dishes in Each Menu:
- Each menu must feature unique dishes, ensuring no repetition of the same dish.
4. Limited Use of Similar Color and Texture Dishes:
- Dishes with the same color and texture should not appear more than twice in a single menu.
5. No Salad with Vegetable Dishes:
- Salad should not be served alongside vegetable dishes to ensure nutritional variety.
6. No Compote or Stewed Fruits with Soups:
- Compote or stewed fruits should not accompany soups.
7. No Rice with Stuffed Meat Dishes:
- Rice dishes should not be served with stuffed meat dishes.
8. No Combination of Rice Pilaf, Yogurt Soup, and Rice Pudding on the Same Day:
- Rice pilaf, yogurt soup, and rice pudding should not be included in the same day's menu.
9. Nutritional Value Limits:
- The nutritional values of menu items must fall within specified limits for carbohydrates, protein, fat, fiber, and energy.
10. User Preferences Consideration:
- Menus should be optimized based on user preferences collected through demographic and food preference surveys.

FINDINGS AND DISCUSSION

The menu planning software developed in this study has yielded successful results based on various tests and evaluations. The findings are as follows:

First test: Responses from 500 users were randomly generated and optimized. The optimization results were positive, with all constraints being met. The comparison of menus optimized with and without AI shows the effectiveness of the AI model in improving the menu planning process.

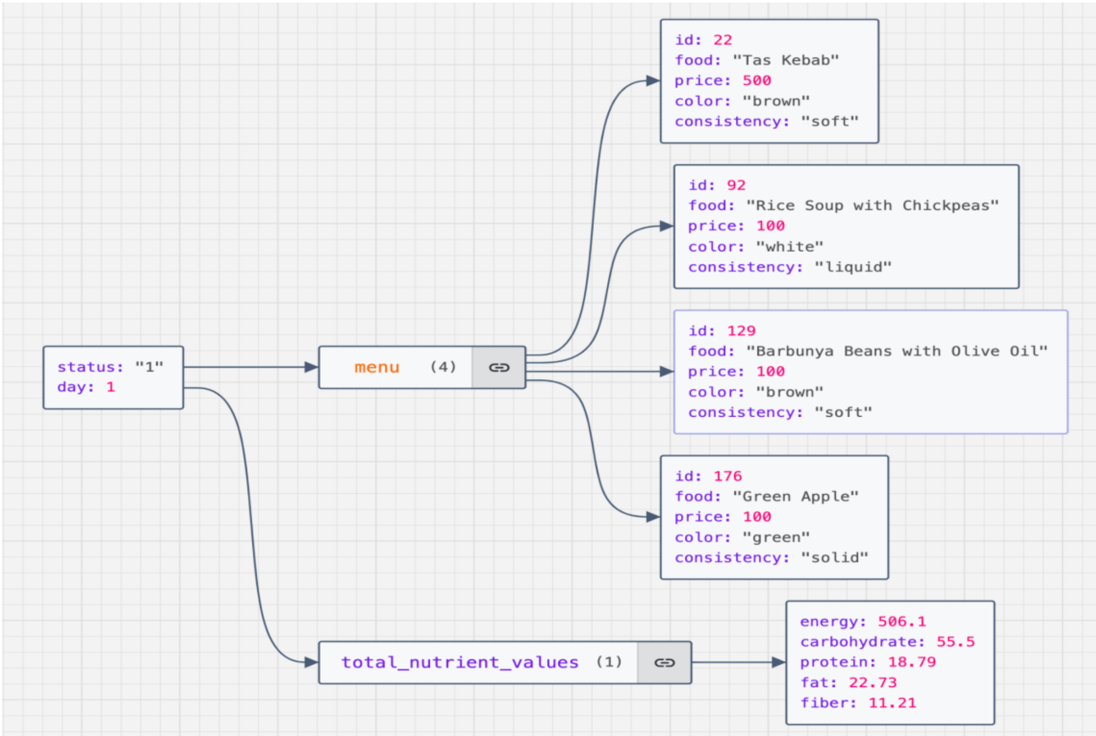

Figure 2. Menu optimized with user preference data without using AI

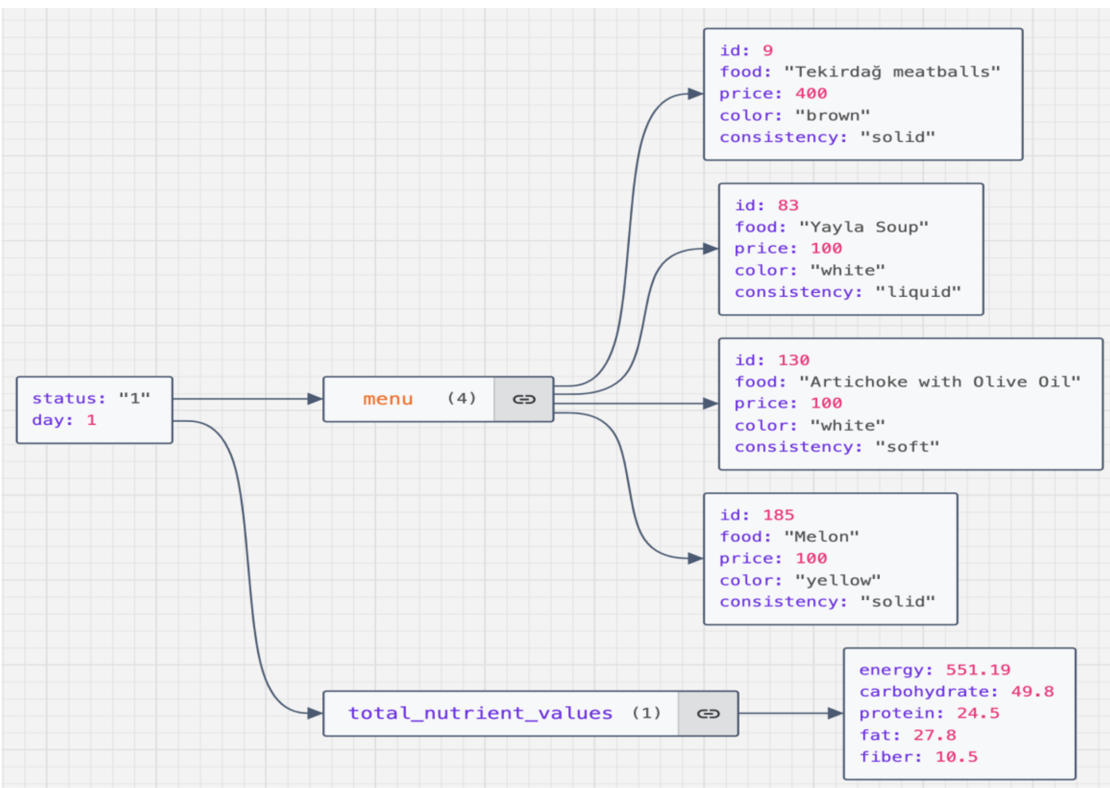

Figure 3. Menu optimized with user preference data using AI

Second test: Responses from 5000 users were randomly generated and optimized. Again, all constraints were met, demonstrating the AI model's efficacy. The optimized menus and score metrics confirm the benefits of incorporating AI in the optimization process.

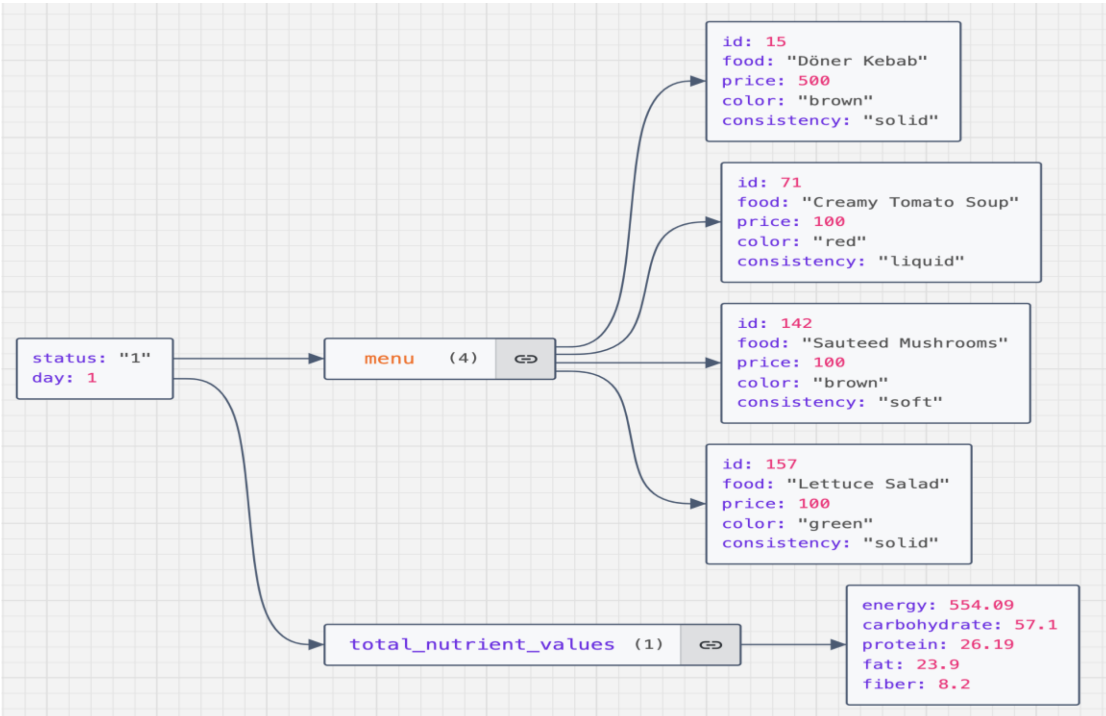

Figure 4. Menu optimized with user preference data without using AI

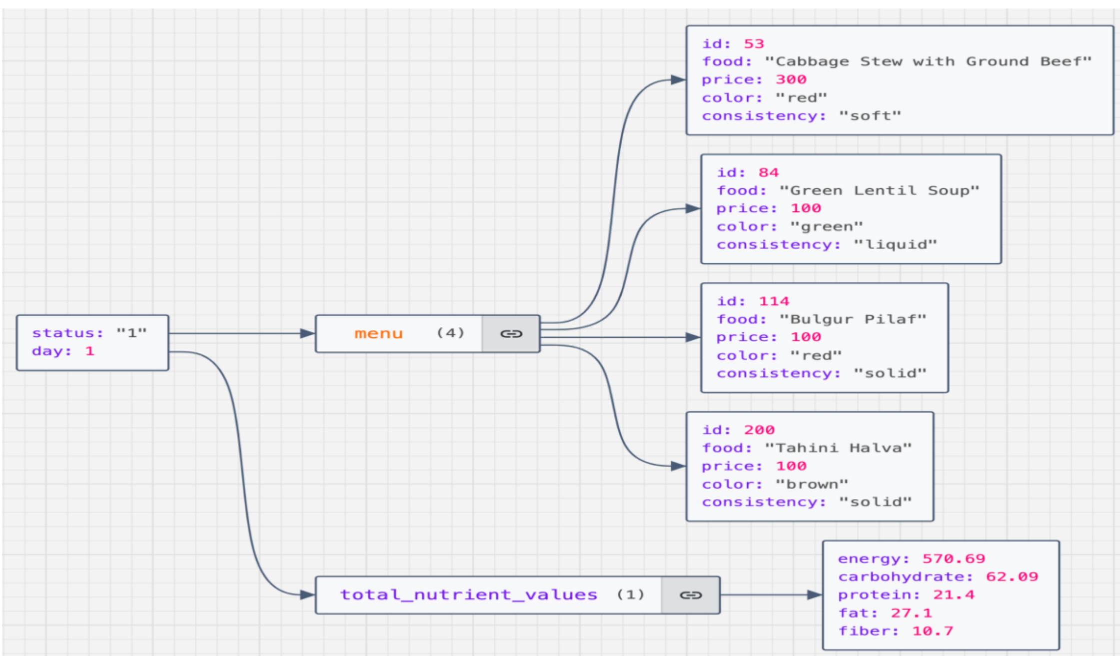

Figure 5. Menu optimized with user preference data using AI

Third test: Responses from 15000 users were randomly generated and optimized. The optimization process successfully met all constraints. This test was conducted to evaluate the impact of dataset size on model performance.

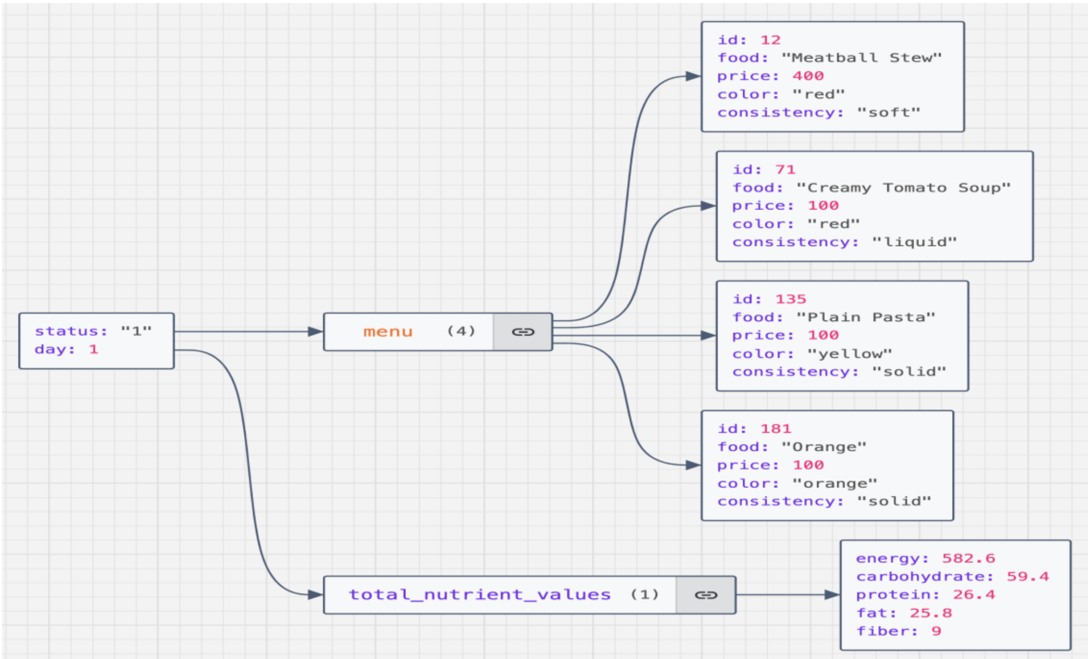

Figure 6. Menu optimized with user preference data without using AI

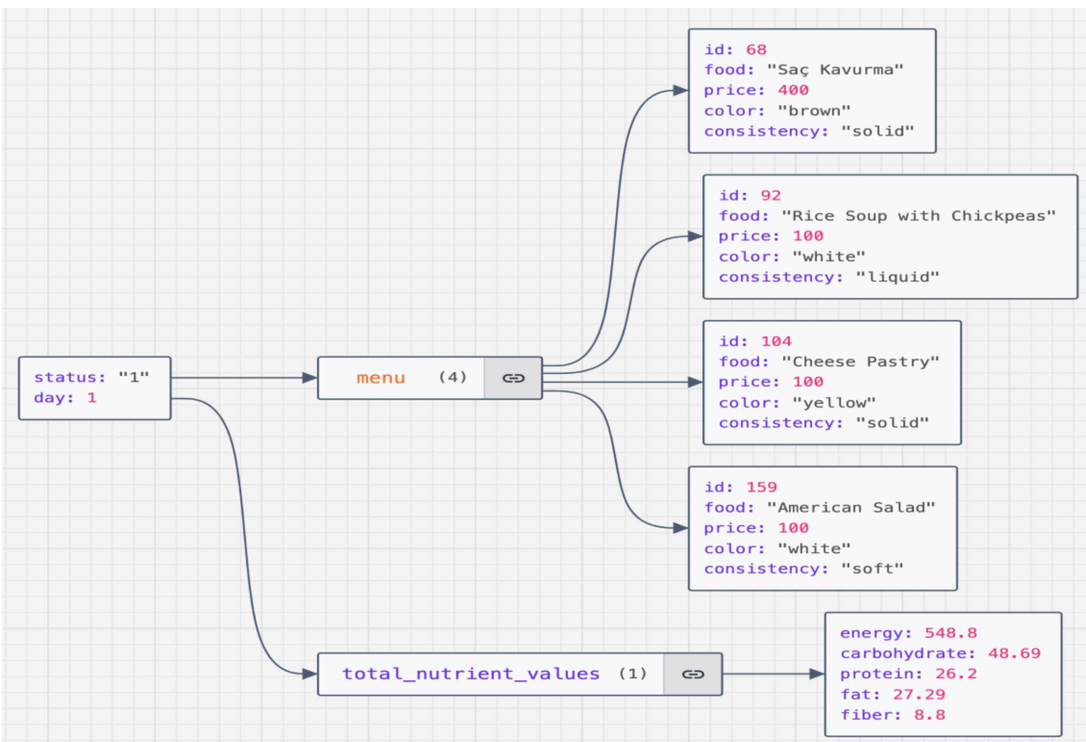

Figure 7. Menu optimized with user preference data using AI

A high Accuracy, Precision, Recall, F1 Score indicates that the model is performing well. Low Precision indicates that the number of false positive predictions is high, while low Recall indicates that the number of false negative predictions is high. Ideally, the aim is to achieve a high F1 Score with high Precision and Recall. Accuracy: Shows the correct rate of all predictions. Precision: Shows how many of the samples predicted as positive are actually positive. Recall: Shows how many of the true positive samples were predicted as positive. F1 Score: Takes the harmonic average of the Precision and Recall value and provides a balanced performance measure. The test results indicated that increasing the dataset size does not always lead to performance improvement. Instead, as the dataset size increased, a decline in accuracy and other performance metrics was observed:

Table 3. 500 Users Metric Values

Metric	Value
Accuracy	22
F1-Score	21.86
Recall	23
Precision	22

Table 4. 5000 Users Metric Values

Metric	Value
Accuracy	20.27
F1-Score	20.11
Recall	20
Precision	20

Table 5. 15000 Users Metric Values

Metric	Value
Accuracy	19.55
F1-Score	19.54
Recall	19
Precision	19

These findings suggest that more qualitative and representative data are needed to improve model performance. Future work may focus on techniques such as data preprocessing, feature engineering, and model optimization to enhance the AI model's performance.

CONCLUSION

This study focused on developing software for catering companies by using optimization and artificial intelligence algorithms. The primary aim was to offer customized menus tailored to users' dietary habits and preferences, thereby achieving optimal solutions for both health and satisfaction. The conducted tests revealed that combining artificial intelligence and optimization techniques enables the creation of user-focused menu plans. However, the performance of the AI models was below expectations, with a significant drop in accuracy as the dataset size increased. This suggests that the model struggled with predictions due to greater diversity and complexity. The contributions of this work to the literature and practical applications include the effective use of LP and MILP techniques for creating optimal menus by considering nutritional constraints and user preferences. Additionally, integrating AI techniques has provided significant advantages in offering personalized solutions. Nonetheless, the low model performance underscores the need for further data and model improvement efforts. In the context of menu planning, data privacy and user consent are important. User data is securely encrypted and stored, with access limited to authorized personnel only. When necessary, data is anonymized to protect user identities and ensure privacy in case of potential data breaches. Users are informed about what data is collected and how it is used, with full transparency regarding data usage policies, privacy policies, and terms of service. Additionally, users have the right to delete their personal data at any time, enhancing data privacy and user control. Maintaining these high standards is a critical step in earning and sustaining user trust. Future studies should aim to use more qualitative and representative datasets to enhance model performance. Optimizing AI models with advanced techniques and comparing different algorithms will also be beneficial. Moreover, continuously improving the system with user feedback and increasing user satisfaction should be a key focus for future studies. In summary, this study has demonstrated how optimization algorithms and AI techniques can be utilized in personalized menu planning. The findings highlight the potential of these techniques while also emphasizing the need for improved model performance and larger datasets. Future research in this area can significantly contribute to the development of personalized nutrition solutions by exploring and expanding the scope of investigations.

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