Jheronimus Academy of Data Science

Reduce Food Waste and Generate Healthy Diet Plans Using LLM

MealMind - An Itelligence PlanApp

Shen Jikun

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Contents

Abstract

Food waste remains one of the most urgent sustainability challenges worldwide, with over 1.3 billion tonnes of food discarded annually. Retailers contribute significantly to this waste, while consumers often lack tools to utilize surplus food efficiently. Simultaneously, many individuals struggle to plan nutritionally balanced meals suited to their lifestyles. To address both issues, this study introduces **MealMind**, an AI-powered application that combines food waste reduction with personalized meal planning. MealMind comprises two key modules: (1) **Eco Meal Maker**, which recommends recipes based on user-inputted keywords, cuisine preferences, or abstract ideas, using a FAISS index built on vectorized recipe keywords to match surplus food items to feasible meals; and (2) **Fit Meal Planner**, which tailors meal plans to individual weight and daily activity schedules by estimating nutritional requirements and selecting optimal recipe combinations. The system utilizes embedding models (OpenAI's `text-embedding-3-small`) and language models (DeepSeek-R1) for semantic understanding, coupled with nutritional data from prior research. While promising, current limitations include lack of support for allergies, limited scalability for group planning, and performance inefficiencies in recipe combination logic. MealMind demonstrates the potential of integrating language models and food databases for promoting sustainability and personalized health, paving the way for future intelligent food management systems.

1 Introduction

Food waste is a widespread and persistent global issue. Each year, approximately 1.3 billion tonnes of food—about one-third of all food produced for human consumption—is wasted[3]. A significant portion of this waste originates from food retailers, who often discard edible products due to overstocking, aesthetic standards, or logistical inefficiencies.[2]This not only represents a substantial loss of resources but also contributes to environmental degradation, particularly through the emission of greenhouse gases as food decomposes in landfills.

This problem has attracted growing attention across sectors. Efforts to reduce food waste are not limited to humanitarian goals such as alleviating food insecurity in regions like Rwanda; they have also become a priority in political and policy discussions across developed nations. For instance, governments across Europe, including the Netherlands, have introduced national strategies and policies aimed at minimizing food waste at various stages of the supply chain. These initiatives underline the urgency and complexity of the issue, and the need for innovative, technology-driven interventions.

This thesis focuses on a specific aspect of the broader food waste problem: the gap between surplus food availability and actual consumer use. While retailers often possess ingredients that are still fit for consumption, they lack tools to repurpose them efficiently. Simultaneously, consumers may have limited knowledge or time to transform surplus food into nutritious meals that suit their preferences and daily schedules. Bridging this gap could significantly reduce waste while promoting healthier eating habits.

To address this challenge, this project introduces **MealMind**, an AI-powered software application designed to support both food retailers and consumers. The core idea behind MealMind is to leverage large language models (LLMs) to make surplus food more usable and accessible. The system consists of two integrated components:

- The **FitMeal Planner**, which generates personalized meal plans based on users' schedules and nutritional requirements;

- The **EcoMeal Maker**, which suggests recipes using surplus ingredients while aligning with users' flavor preferences.

The underlying hypothesis is that by making it easier for consumers to plan meals that are both healthy and resource-efficient, and by enabling retailers to better circulate surplus ingredients, it is possible to meaningfully reduce food waste.

This thesis explores the following research question:

How can a large language model (LLM) effectively generate personalized meal plans based on customers' schedules and retrieve recipes based on customers' flavor preferences using surplus food ingredients?

In the following chapters, the thesis will elaborate on the theoretical and practical basis for this approach. A review of existing literature will explore prior work on food waste reduction, AI applications in nutrition and meal planning, and the role of recommender systems in sustainable consumption. The aim is to position this work within ongoing academic and applied research efforts, and to identify the contributions and innovations that distinguish this project.

1.1 Related Works

Several existing services and studies address components relevant to this project, particularly in the domains of food waste reduction and personalized nutrition. To mitigate food waste, food retailers typically adopt a combination of technological, operational, and social strategies.[4]However, these approaches often remain fragmented and unidirectional, focusing primarily on inventory management rather than consumer engagement or intelligent reuse of surplus food.

In the context of promoting healthier lifestyles through improved dietary behavior, a number of commercial products offer related functionalities. For instance, **PlateJoy** provides personalized meal plans and recipes based on user preferences, with the goal of saving time and supporting healthy eating habits. Similarly, **Eat This Much** generates meal plans customized to users' dietary goals, preferences, budgets, and schedules. While these platforms contribute to personalized nutrition, they do not directly address food waste, and often come with subscription fees that limit accessibility. Furthermore, their recommendation logic lacks transparency and adaptability when integrating surplus or non-standard food items into meal suggestions.

This project seeks to bridge these gaps by proposing an integrated, AI-powered system that simultaneously targets food waste reduction and personalized health optimization, grounded in users' real-life schedules, ingredient availability, and taste preferences.

2 Approach

2.1 Data Preprocessing

Figure 1: Original Dataset

The first original dataset, related to food waste (Figure 1), was obtained from Drik, a supermarket chain operating 121 stores across the Netherlands.

This dataset contains records of food products that were discarded. From this dataset, product names associated with wasted food items were extracted for use in recipe matching. After removing duplicate entries and records with missing product names, a total of 22,417 unique product names remained. Examples of the product name format are presented in Table 1.

product name
*30mm Zwart
*35mm Donkerbruin
*35mmzwart Dark Nikkel
*40mm Zwart

Table 1: product name

The second original dataset, consisting of recipes, was scraped from Allerhande, a Dutch online recipe platform. The collected data includes dish names, portion sizes, nutritional information, ingredient lists, relevant keywords, and URLs, all compiled into a structured CSV format. The corresponding column schema is shown in Table 2. After eliminating incomplete entries (using a drop-na procedure) and removing duplicates, 21,910 valid recipe records were retained.

Name	Persons	Nutrients	Ingredients	URL	Key word

Table 2: Columns

To integrate these two datasets, a matching process was conducted between surplus product names and recipe ingredients. For this purpose, the **text-embedding-3-small** model from OpenAI was used to embed both product names and ingredient names into high-dimensional semantic vector spaces. Cosine similarity was then calculated between each product name and each recipe ingredient. If the similarity score exceeded a threshold of 0.6, the product and ingredient were considered a match. A recipe was deemed to be "matched" and thus usable if at least 80 per cent of its ingredients could be matched to products from the surplus dataset.

recipe name	Apple pie(matched)	Pear pie(not matched)
ingredients	apple,sugar,flour,oil,egg	pear,sugar,flour,oil,egg

Table 3: recipe example

Surplus Product
Ashmead's Kernel apple,Diamant sugar,Olitalia oil,AH Verse egg

Table 4: waste product example

Here is an example of how it works. We use the waste product example (table 4) as input and get a mapped ingredients result:apple,sugar,oil,egg. Clearly,4/5 of the apple pie ingredients are matched, but only 3/5 of the pear pie ingredients are matched (table 3). Thus apple pie is matched but pear pie is not. Through this approach, a total of 16,835 recipes were identified as viable for preparation using surplus food items. This filtering step directly supports the project's goal of enabling the repurposing of wasted food into practical meals.

2.2 Main Functionalities

The proposed system, *MealMind*, is designed with two core functionalities to address the dual challenges of food waste reduction and personalized nutrition: the **FitMeal Planner** and the **EcoMeal Maker**. Each module targets a specific user need while contributing to the overarching goal of sustainable and health-conscious meal generation.

2.2.1 Eco Meal Maker

The **EcoMeal Maker** module is designed to recommend recipes based on flexible and subjective user inputs, thereby enhancing user engagement and promoting the use of surplus food in a personalized manner. Unlike traditional recipe search systems that rely on exact ingredient matching or fixed filters, this module allows users to express their preferences in natural language. Inputs may range from specific dish names (e.g., "chicken curry"), to cuisine types or flavors (e.g., "spicy" or "Mediterranean"), or even abstract impressions such as "light and refreshing" or "comfort food."

To implement this functionality, a semantic search pipeline was constructed using OpenAI's `text-embedding-3-small` model and the FAISS (Facebook AI Similarity Search) library. The implementation consists of the following steps:

1. **Vectorization of Recipe Keywords**:

   All recipes in the database were preprocessed by extracting their `keywords` column, which captures core semantic features of each dish. These keywords were embedded into high-dimensional vector representations using the `text-embedding-3-small` model. The resulting vectors were indexed using FAISS to enable efficient similarity search. Other relevant recipe attributes (e.g., title, ingredients, nutritional information) were stored as metadata associated with each indexed vector.

2. **User Query Embedding and Retrieval**:

   When a user enters a free-form query indicating what they would like to eat, the system first transforms this input into a vector using the same embedding model. It then queries the FAISS index to retrieve the top-k most semantically similar recipe vectors, where k is determined by the number of dishes the user wishes to receive.

3. **Result Filtering and Output**:

   The retrieved recipes are filtered and ranked based on semantic similarity scores. Optionally, filters such as preparation time, dietary constraints, or available surplus ingredients can be applied at this stage. The final output consists of k recommended recipes that best match the user's expressed preferences.

In addition to the semantic recommendation logic, the *EcoMeal Maker* offers an intuitive and minimal user interface designed for flexible input and quick feedback. As illustrated in Figure2, users are invited to describe what they feel like eating—ranging from specific dishes to abstract concepts—via a free-text input field. They can also specify how many recipe suggestions they wish to receive. Upon submission, the system returns a curated list of recipes that semantically match the input, drawing from surplus-compatible meals. This interface lowers the barrier for user engagement and makes the recipe discovery process more enjoyable and adaptive.

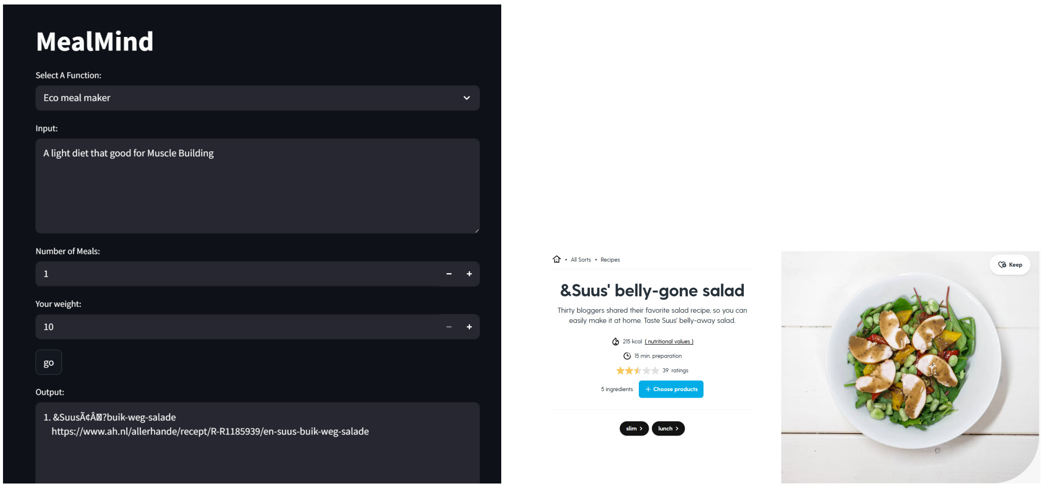
This semantic search-based approach allows for flexible, intuitive interactions with the system and enhances the repurposing of surplus food by aligning it with user intent in a more natural and engaging way.

2.2.2 Fit Meal Planner

The Fit Meal Planner module aims to generate daily meal combinations that align with a user's personal nutritional requirements, derived from their weight and daily activity schedule. This approach integrates both physical health considerations and food sustainability by promoting surplus ingredient usage in a goal-oriented way.

Functional Overview

As shown in Figure 3 , users are prompted to input:



(a) User input interface (b) Recipe results

Figure 2: EcoMeal Maker interface: from query input to personalized recipe results.

- Body weight (in kilograms)
- Daily activity schedule, in free-text format (e.g., "1 hour jogging in the morning, 30 minutes cycling to work, and desk work for 6 hours")
- Number of dishes (k) they wish to receive

The system outputs a set of k recipes whose combined nutritional content closely matches the user's calculated requirements for protein, carbohydrates, and fat.

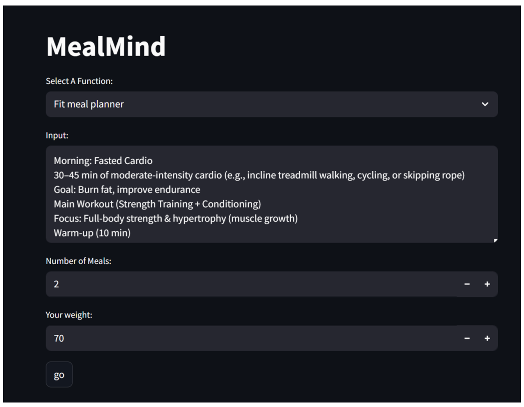


Figure 3: User input interface for Fit Meal Planner

Technical Implementation

The implementation involves the following key steps:

1. **Activity Classification and Nutrient Mapping**:

   Based on [1], all physical activities are classified into three intensity levels: low, moderate, and high. Each intensity class is associated with per-minute, per-kg nutrient requirements for protein, carbohydrates, and fat, as shown below:

   - Protein (g/kg/min): low = 0.0033, moderate = 0.0050, high = 0.0067
   - Carbohydrates (g/kg/min): low = 0.0018, moderate = 0.0012, high = 0.0015
   - Fat upper limit (g/kg/min): low = 0.0066, moderate = 0.0110, high = 0.0076

2. **Semantic Activity Parsing with DeepSeek-R1**:

   The user's free-text daily schedule is parsed using the deepseek-R1 large language model, which semantically maps natural language descriptions of activities to structured time allocations per intensity class. For example, a sentence like "I walked to work for 30 minutes and did yoga for an hour" would be parsed as:

   - 30 minutes of low-intensity activity
   - 60 minutes of moderate-intensity activity

3. **Nutritional Requirement Calculation**:

   Given the user's body weight w(in kg) and total time t_i per activity level i in (low,moderate,high), the required nutrients are calculated by:

   $$\begin{aligned} \text{Protein}_{\text{ total}} &= w \cdot \textstyle\sum_i t_i \cdot p_i \\ \text{Carbohydrates}_{\text{ total}} &= w \cdot \textstyle\sum_i t_i \cdot c_i \\ \text{Fat}_{\text{ max}} &= w \cdot \textstyle\sum_i t_i \cdot f_i \end{aligned}$$

   where p_i, c_i and f_i represent per-minute nutrient coefficients for protein, carbohydrates, and fat respectively.

4. **Recipe Combination Search**:

   From the preprocessed recipe database (each record containing nutrient values per portion), the system selects combinations of k dishes whose summed nutrition values are within a 10 per cent error of the target nutrient profile.

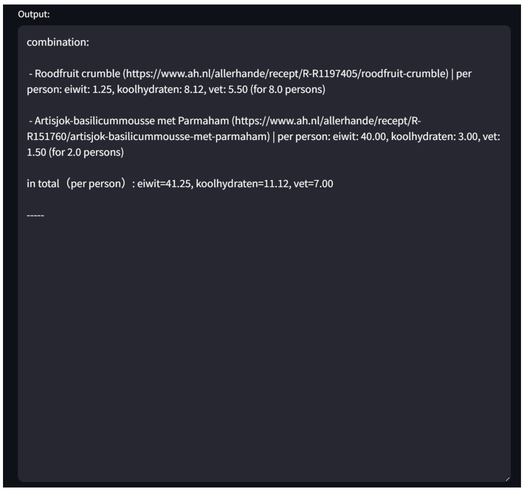


Figure 4: System output with matched recipes and nutritional breakdown

5. **Output**:

   The system returns a personalized meal plan with k recipes whose combined nutrient contents approximate the user's daily needs. An example output is shown in Figure 4, where two recipes are selected along with their nutritional breakdown and source links. This not only helps users meet health goals but also leverages surplus-based recipes, contributing to waste reduction.

3 Limitations, and Future Work

3.1 Limitations

First, the Eco Meal Maker currently lacks personalization features such as dietary restrictions, allergen avoidance, or cultural preferences. As a result, users with specific needs (e.g., gluten-free or nut-free diets) may receive unsuitable recommendations.

Second, the Fit Meal Planner module is currently designed to generate a daily meal plan for a single user. It does not yet support multi-user or family-level planning, nor does it account for different dietary goals (e.g., weight loss, muscle gain) across individuals in a household.

From a performance standpoint, Eco Meal Maker benefits from the use of a FAISS index for fast nearest-neighbor search, providing real-time recommendations even with a large recipe dataset. However, the Fit Meal Planner employs a brute-force linear search strategy to find meal combinations that match calculated nutritional needs. This results in significant delays when the user requests more than three meals (k¿3), as the system must evaluate all possible combinations exhaustively.

3.2 Future Work

To address these limitations, future work will focus on the following directions:

- **User personalization**: Integrating user profiles with preferences, allergens, and nutritional goals to provide more tailored recommendations in both modules.
- **Group-based planning**: Extending the Fit Meal Planner to support multi-person meal planning by aggregating and balancing nutritional needs across multiple users.
- **Optimization algorithms**: Replacing the brute-force search in the Fit Meal Planner with more efficient methods such as dynamic programming, constraint satisfaction, or genetic algorithms to improve scalability and runtime performance.
- **Feedback loop and learning**: Allowing users to provide feedback on meal suggestions to fine-tune future recommendations using reinforcement or preference learning techniques.

By addressing these aspects, the system can evolve into a more robust and adaptive tool for promoting healthy eating and reducing food waste at scale.

4 Conclusion

This study presents MealMind, an AI-driven system designed to address two pressing challenges: reducing food waste in the retail sector and promoting healthier dietary habits through personalized meal planning. By leveraging large language models and vector-based semantic search, the system offers two functional modules—Eco Meal Maker and Fit Meal Planner—that tackle different aspects of the problem.

The Eco Meal Maker allows users to receive recipe recommendations based on vague or specific food-related queries, repurposing surplus ingredients from food retailers. This is achieved by embedding recipe keywords into vector space and conducting fast similarity search using FAISS indexing.

On the other hand, the Fit Meal Planner generates customized meal combinations based on users' daily schedules and physical activities. By semantically interpreting user routines and mapping them to nutritional requirements, the system recommends meals that meet calculated dietary needs using a recipe database.

The integration of semantic understanding, nutrition science, and food waste data showcases the potential of AI in creating practical tools for sustainability and public health. While limitations remain in personalization, scalability, and performance optimization, the system lays a strong foundation for future development in intelligent meal planning and food waste reduction.

In conclusion, MealMind demonstrates how modern AI technologies can bridge the gap between food surplus and dietary personalization, offering a novel approach to sustainable and health-conscious living.

References

[1] Adam Amawi, Walaa AlKasasbeh, Manar Jaradat, Amani Almasri, Sondos Alobaidi, Aya Abu Hammad, Taqwa Bishtawi, Batoul Fataftah, Nataly Turk, Hassan Al Saoud, Amjad Jarrar, and Hadeel Ghazzawi. Athletes' nutritional demands: a narrative review of nutritional requirements. *Frontiers in Nutrition*, Volume 10 - 2023, 2024.

[2] Jessica Aschemann-Witzel, Ilona De Hooge, Pegah Amani, Tino Bech-Larsen, and Marije Oostindjer. Consumer-related food waste: Causes and potential for action. *Sustainability*, 7(6):6457–6477, 2015.

[3] Karin Schanes, Karin Dobernig, and Burcu Gözet. Food waste matters - a systematic review of household food waste practices and their policy implications. *Journal of Cleaner Production*, 182:978–991, 2018.

[4] Felipe Vizzoto, Francesco Testa, and Fabio Iraldo. Strategies to reduce food waste in the foodservices sector: A systematic review. *International Journal of Hospitality Management*, 95:102933, 2021.