Utilising Text Mining Techniques for Personalised Diet Recommendations using Heterogeneous Data

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This project aims to develop a personalised diet recommender system by leveraging text-mining techniques to extract insights from diverse data sources. Datasets comprising structured, semi-structured, and unstructured nutritional information and recipes, with the latter scraped using the Beautiful Soup library, are utilised to offer tailored meal plans matching individual needs. Word2Vec is also implemented for ingredient extraction from recipe data. The implementation identifies ingredients, calories, and nutritional values while considering users' Basal Metabolic Rate (BMR) and preferences. Collaborative filtering is explored for recommending similar recipes based on user data. A Proof of Concept, developed using Next.js and deployed on https://ics5111.vercel.app/, showcases intelligent meal plan recommendations. This prototype was well-received in a usability study, with an average SUS Score of 93.25

CCS Concepts: • **Computing methodologies** → **Supervised learning by classification**; • **Theory of computation** → **Nearest neighbor algorithms**; • **Information systems** → *Data cleaning*.

Additional Key Words and Phrases: Data Mining, Diet Recommender, Digital Health, Word2Vec

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1 INTRODUCTION

The rise of chronic diseases, attributed to unhealthy lifestyles and dietary choices, poses a significant global health challenge. The World Health Organization (WHO) reports that chronic diseases account for a staggering 74% of global mortality, highlighting the urgent need for interventions to promote healthier eating habits [7, 12, 17]. As individuals increasingly seek personalised dietary strategies, they face the challenge of sifting through the vast array of food options and ingredient combinations possible, compounded by a lack of nutritional knowledge [6, 8, 13]. Consequently, there is a growing interest among researchers in leveraging data-driven methodologies to refine meal planning and nutritional guidance [6, 13, 20], with ongoing efforts aimed at optimising these approaches further.

The convergence of health and technology offers a promising avenue to address this public health issue. Advanced techniques can allow us to harness diverse data sources and unlock valuable insights to provide intelligent, user-tailored dietary recommendations. These meal recommendations can be finely tuned to individual goals [6], Body Mass Index (BMI), dietary restrictions, and personal preferences, empowering individuals to make informed dietary choices and improve their overall health [5].

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This study delves into the use of different data types with several techniques including text mining [18] and collaborative filtering [24], to develop the capability of providing nuanced, personalised meal plans.

1.1 Aims and Objectives

The primary aim of this project is to develop a context-aware and effective intelligent diet recommendation system by integrating different types of data sources, aiming to provide a more holistic understanding of users' dietary needs and personal preferences. To achieve this, the following objectives were determined:

- The gathering of structured, semi-structured, and unstructured data such as recipes and health-related data through various models to create a robust tool for providing users with relevant meal plans.
- Leveraging text data mining and Natural Language Processing (NLP) techniques, particularly Word2Vec, to extract meaningful insights from textual data sources such as recipes and nutritional databases.
- Designing an interactive and user-friendly dashboard, empowering individuals to tailor their dietary plans based on personal preferences and restrictions.
- Evaluating the performance and usability of the recommender and dashboard through user testing and feedback mechanisms.

2 RELATED WORK

Recommendation systems have been used as an effective remedy for the overload of information users encounter, being an easy tool to filter vast datasets to deliver content pertinent to user-defined criteria [15, 23]. The application of these systems, often integrated with Machine Learning (ML) models, spans various domains such as commerce, education, and more recently, healthcare [23]. Notably, recent research endeavours have concentrated on the development of personalised decision support systems tailored to creating meal plans based on nutritional information [2, 5, 11, 22, 23].

Tao et al. [18] explored the use of text mining techniques on different dataset types containing nutritional information and recipes, including word-level analysis, text classification, text clustering and word association analysis. The study provides insight into viewing hidden patterns by analysing big data for more intelligent decision-making.

Many studies have discussed and made us of K-means clustering to identify patterns and partition the dietary data to evenly cluster the food [8, 11, 22, 24], with Kardam et al. [8] clustering according to calories.

Apart from K-means clustering, Metwally et al. [11] employed the use of Word2Vec to generate word embeddings, which was pre-trained on a Google News database and fine-tuned using artificial sentences which concatenated descriptive food named and their respective food categories. By calculating the cosine similarity between the embeddings, the system identified the most similar food items and assigned them labels based on predefined categories. This method achieved promising results, managing to identify a significant portion of a user's most frequently eaten foods.

To recommend meals, Harvey et al. [6] and similar studies calculated users' nutritional needs based on Basal Metabolic Rate (BMR) and diet objectives. Recipes meeting these criteria were categorised by a recommendation level and divided for breakfast and main meals. An earlier study by the same author highlighted the importance of user taste when recommending meals and the understanding of what factors influence how people rate recipes, enhancing the accuracy of their approach over simpler methods like average ratings and nearest neighbour algorithms [7].

Yang et al. [22] created a framework to learn food preferences from item-wise and pairwise image comparisons to develop a meal recommender system that meets user's nutritional expectations. This model achieved a higher level of preferred recommendation, adjusting itself to users' preferences based on the information gathered.

Meanwhile, Yuan and Luo [24] presented the use of a collaborative filtering model based on user preferences for dietary recommendations. Their approach involves setting a threshold, constructing user-diet frequency matrices, calculating diet preference matrices, and determining Pearson similarity between users. They then select neighbours with the highest similarity, identify clusters of standard recipes, and recommend dishes based on their recommended values, considering users' dietary records and preferences.

Stefanidis et al. [17] focused on the development of a knowledge-based recommendation framework for personalised nutrition. This approach leverages a qualitative layer for verifying ingredient appropriateness and a quantitative layer for synthesising meal plans based on target nutrient values and ranges. By adopting a 2-layered architecture, the system disentangles the appropriateness of meals from that of meal plans, allowing independent evaluation of every subsystem.

3 DESIGN AND IMPLEMENTATION

In this section, we will be discussing the steps taken to implement the prototype developed for this project, which was deployed on https://ics5111.vercel.app/, with the code base available on GitHub (https://github.com/NathanPortelli/Ics5111-Mining-Large-Scale-Data/).

3.1 Data Collection and Handling

Various data sources were used for the development of the Proof-of-Concept (POC). These data sources can be broadly categorised into structured, semi-structured, and unstructured datasets. Each type of data was collected, cleaned where necessary, and pre-processed to prepare it for use in the developed prototype.

3.1.1 Structured Data. Structured data forms the bedrock of this project, empowering the implementation of our Word2Vec model and facilitating streamlined user preference categorisation. These datasets comprise the following:

- **Stopwords:** A text file containing a list of stopwords in the English language [3]. These stopwords are utilised to filter out common words that do not carry significant semantic meaning in the context of text analysis. This filtering process helps streamline the text-mining operation by focusing on words that contribute meaningfully to the analysis while disregarding irrelevant terms that may skew the results. The list was added to a Firestore collection to be used within the text mining process.
- **FoodData Central - Foundation Foods:** FoodData Central (FDC) is an integrated database system offering readily accessible information on foods and food components [19]. It includes data regarding foundation foods, encompassing nutrient values and underlying metadata on food ingredients and types [4, 10]. This dataset, sourced from a CSV file, underwent cleaning and pre-processing before being utilised in our POC. Grouping different item types and categories facilitated the identification of core nutritional components and established a baseline for nutritional analysis and comparison within the context of dietary recommendations.
- **User BMI and Preferences:** To lay the groundwork for collaborative filtering, data on user demographics and meal preferences were collected from a sample of 64 individuals. Each participant provided information on their gender, age, height, weight, and preferences for food types during breakfast, lunch, and dinner. This data was saved to the "users" collection on Firestore.

3.1.2 Semi-structured Data. The Spoonacular API serves as an extensive culinary database, offering thousands of recipes accompanied by comprehensive data for each entry [16], including instructions, ingredients, nutritional information and calorie counts. enables dynamic retrieval of recipe data, allowing for personalised meal recommendations aligned with individual preferences, BMR, and dietary goals. The implementation involves making API requests to fetch recipe data based on user-defined parameters like meal types and calorie requirements. Upon receiving the JSON response, the data is parsed and processed to extract relevant information such as recipe titles, images, and calorie counts per meal. This user-friendly interface enables seamless navigation and exploration of culinary options tailored to their preferences.

3.1.3 Unstructured Data. The unstructured data utilised in this project was obtained by scraping Jamie Oliver's website (https://www.jamieoliver.com/) using Python and the Beautiful Soup library which facilitated the extraction of recipes, including details such as recipe names, ingredients, instructions, and nutritional information. Cleaning and pre-processing were necessary to address missing values, duplicates, and inaccuracies in the scraped data, which was then converted to JSON format. By leveraging these scraped recipes, users are presented with alternative options similar to the ones presented to them from the Spoonacular API that still align with their dietary preferences and health goals, thus enhancing the overall user experience and promoting engagement with the system.

3.2 Design Architecture

The core of the system lies in its ability to provide intelligent diet recommendations to users. This process involves the integration of various data sources mentioned above to generate tailored meal plans. The system analyses user inputs such as health goals, dietary restrictions, and general preferences, and makes use of food categorisation, Spoonacular API, a custom Word2Vec implementation, and recipes from Jamie Oliver's website as alternate meal plans.

3.2.1 Web Scraping. Jamie Oliver's website hosts a large collection of diverse recipes, each accompanied by detailed information including ingredients, recipe steps, calorie count and various types of nutritional values per serving. Recipes are organised into specific food categories, simplifying the scraping process by providing structured sections for each recipe. The 'Ingredients' category was chosen for iteration due to its abundance of unique recipes and minimal duplicate data, facilitating straightforward food categorisation during scraping.

A Python script was created to ease the scraping process, utilising the Beautiful Soup [14] and requests libraries to parse HTML codes and extract pertinent data elements from HTML tags and attributes. The scraped data included the recipe title and subheading, link to the recipe image, serving size, introductory paragraph, calorie count, nutritional values, ingredients, and the recipe method. Of this information, the title, image link, calorie count, ingredients, and recipe steps were kept for the scope of this project, which were then cleaned from duplicate recipes and missing values. The remaining recipes were combined and stored in CSV format, which was then reformatted into JSON for easier importation and manipulation by other modules.

3.2.2 Word2Vec. The Word2Vec implementation, developed using Typescript and inspired by [9, 21], serves two distinct purposes. Initially, it extracts recipe titles to offer alternative recipes to users. Secondly, it parses ingredients from recipe instructions. Before passing the respective data to the model, both use cases first handle a series of text pre-processing, including removing white space, stop-words and HTML and Markdown tags. Once that is done, said text is converted into a series of strings that will be added to the model as part of its vocabulary while also initialising their respective word vector. The model is trained using various recipe instructions from the Jamie Oliver dataset and the added sentences. Using the aforementioned 'Foundation Foods' dataset, ingredients are extracted from either the recipe title or recipe instructions, respective to the use case, by matching word vectors.

3.2.3 Collaborative Filtering. To further enhance personalisation, collaborative filtering techniques could be used to leverage user feedback to identify similar users and their preferred meal options. The collected user data would then be subjected to clustering algorithms that group users based on their BMI scores, meal preferences and meal-time choices. By analysing user ratings of the provided recommended meal plans, as well as taking note of the selected and unselected meal options, the system would map a connection between similar users [24], thus increasing the likelihood that the provided meals that are more aligned with a user's taste, ensuring a more engaging and effective dietary experience.

Challenges such as the cold start problem, which relates to the difficulty in providing recommendations for new users or items with limited interaction history [24], and scalability issues, where computational complexity increases with the size of the user-item matrix, need to be considered when implementing these techniques.

3.3 Concept Development

For the recommender to provide meal suggestions in a user-friendly manner, we developed an interactive web application dashboard. This dashboard serves as a pivotal component in empowering individuals to personalise their dietary plans and showcasing the capabilities of our diet recommendation model and associated techniques. The Next.js framework was used to develop the dashboard, providing a responsive and efficient platform for users to interact with our system.

3.3.1 Personalised Diet Recommendations. Users can input their health-related information and dietary preferences, the details of which are saved to their account. Based on this information, the recommender generates personalised diet recommendations that align with the provided information.

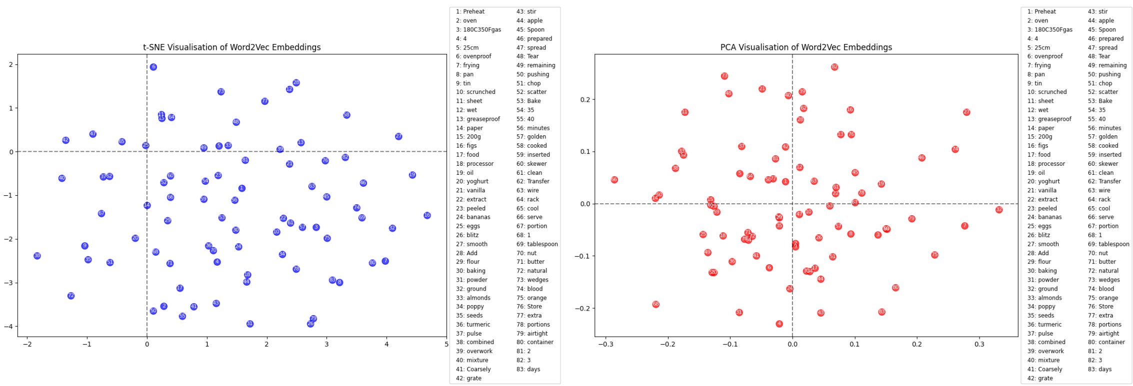
3.3.2 Collaborative Filtering Mechanism. A mock collaborative framework is embedded within the dashboard, intended to simulate the functionality of user mapping. While the system is designed to store users' preferences and selections, the envisioned model would enhance the precision of diet recommendations by leveraging the interactions of users with similar backgrounds and food preferences.

3.3.3 User Experience. We crafted a user-friendly experience with an informative and easy-to-navigate dashboard. Users follow a step-by-step process to generate their personalised meal plan, beginning with inputting their details and preferences and selecting dietary goals. After calculating the recommended daily caloric intake using BMR, users can adjust this recommendation as necessary. The dashboard presents nine potential recipes, three for each meal period: breakfast, lunch, and dinner. Users can explore similar alternatives for each suggested recipe, sourced from Jamie Oliver's site. Once they select one meal for each period and submit their choices, the items are stored in the user's meal history, allowing for easy access to selected recipes, associated ingredients, and recipe steps for future reference.

3.4 Experimentation

3.4.1 Evaluation of Word2Vec Embeddings. The efficacy of the Word2Vec implementation in capturing semantic relationships among words was evaluated using dimensionality reduction techniques such as t-Distributed Stochastic Neighbour Embedding (t-SNE) and Principal Component Analysis (PCA). Trained on recipe instructions, the Word2Vec model represented each word as a vector in a high-dimensional space, capturing semantic similarities based on co-occurrence patterns.

t-SNE and PCA were used to visualise the embedding in lower-dimensional spaces, enabling the exploration of semantic clusters and relationships. The resulting visualisations unveiled clusters of words with similar meanings, signifying successful semantic capture. Figures 1a and 1b depict a t-SNE and PCA plot respectively. Both plots reveal the model's ability to capture some relationships between words, including clustering words related to cooking, baking, and food. However, unrelated words within specific clusters also appear, indicating that the Word2Vec model did not fully grasp the relationship between each word.



(a) t-SNE Visualisation of Word2Vec Embeddings

(b) PCA Visualisation of Word2Vec Embeddings

The analyses offered valuable insights into the embeddings' quality and effectiveness, guiding potential refinements. Through interpreting clusters and patterns, we assessed the model's semantic capture and identified areas for optimisation. As part of the evaluation, ten random recipes from both the Spoonacular Random API (https://spoonacular.com/food-api/docs#Get-Random-Recipes) and Jamie Oliver's collection were selected for evaluation.

A comparison between the actual ingredients of the recipes and the ingredients extracted from the recipe instructions by the Word2Vec model was conducted to generate an accuracy score for ingredient matching. The average accuracy obtained from these ten random recipes was approximately 55%. Considering the limited scope of the food foundations dataset, the Word2Vec model performed reasonably well overall. With a larger food dataset, there would likely be a higher accuracy rate due to the increased likelihood of finding similar word vectors.

3.4.2 User Testings. To evaluate the effectiveness and user-friendliness of the diet recommender system, a usability study was conducted with a group of ten participants. They were asked to complete a series of tasks, including creating an account, providing personal information, selecting meal preferences and diet goals, and evaluating the generated meal recommendations including the alternative options provided for the recommended items.

Overall, the participants found the system easy to use and navigate, appreciating the clear instructions and the intuitive interface design. The majority expressed satisfaction with the meal recommendations, rating them an average of 4 out of 5 using the provided star rating system. While a few meals did not align well with their tastes, participants acknowledged the relevance of the options presented to their dietary preferences. Additionally, the option to request alternative recommendations was well-received, as it allowed participants to tailor the meal plan to their specific tastes.

Some participants suggested including meal preparation time and cooking skill levels with preferences for the meal plans to be closer to their expectations. They also recommended the ability to generate more meals, even if the accuracy of their preferences is reduced. Users also expressed a desire for more diverse alternatives aligned with their preferences. Additionally, some participants expressed a desire for more detailed information about the recommended meals.

The System Usability Scale (SUS) was administered, yielding an average score of 93.25 (see Table 1). According to the adjective rating scale by Bangor et al. [1], this indicates that the system is considered 'excellent' by participants.

Participants	A	B	C	D	E	F	G	H	I	J
I think that I would like to use this system frequently	4	4	4	4	4	4	5	4	4	4
I found the system unnecessarily complex	1	1	1	1	1	1	1	1	1	1
I thought the system was easy to use	5	5	5	5	4	5	5	5	5	5
I think that I would need the support of a technical person to be able to use this system	1	1	1	1	1	1	1	1	1	1
I found the various functions in this system were well integrated	4	5	4	4	4	4	5	4	4	4
I thought there was too much inconsistency in this system	2	1	1	1	1	2	1	2	1	2
I would imagine that most people would learn to use this system very quickly	4	5	5	4	5	5	5	5	5	4
I found the system very cumbersome to use	1	1	1	2	1	1	1	1	1	1
I felt very confident using the system	5	5	5	4	5	5	5	5	5	5
Mean SUS Scores	90	97.5	95	87.5	92.5	92.5	100	92.5	95	90
Total SUS Score	**93.25**									

Table 1. SUS Questionnaire Results

4 CONCLUSION

In conclusion, our project addresses the critical need for personalised nutrition guidance in preventive healthcare. By integrating user profiles, nutritional databases, scraped recipes, and the use of techniques such as Word2Vec, we developed an intelligent diet recommendation system that offers tailored dietary suggestions, empowering individuals to make informed choices about their nutrition. The system's effectiveness was very well-received by participants of the user test, highlighting its potential impact on promoting healthier dietary habits.

4.1 Limitations and Challenges

While the results are promising, the project contains some limitations that should be acknowledged. One significant challenge was the scarcity of publicly available data on meal preferences, which hindered the implementation of suitable user mapping, leading to the creation of a dataset with a small sample size.

In addition, while TypeScript offers powerful capabilities, implementing the Word2Vec model presented challenges. Initially, we explored existing libraries for Word2Vec functionality, but many of these libraries were outdated and incompatible. Consequently, we developed a custom implementation of the technique to address this issue.

4.2 Future Works

While the current iteration of the dashboard and models serve as a robust POC, there is room for future enhancements. Additional information, such as the restriction of particular food types, cooking skill level, budget and time constraints, could be gathered and tested to determine whether they provide meal plans that are more aligned with the users' tastes. Integration with wearable devices for real-time health monitoring and the incorporation of additional ML models may also help refine predictions. Utilising mechanisms for continuous user feedback within the dashboard could help evolve such systems to offer even more sophisticated results.

Moving forward, the area of study holds the potential to contribute not only towards healthier lifestyles but also to aid in the prevention of chronic diseases.

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