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Generative AI-based Meal Recommender System

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Abstract - Maintaining a balanced diet is essential for overall well-being, yet many individuals face challenges in meal planning due to time constraints, limited nutritional knowledge, and difficulty aligning meals with personal dietary needs. Traditional meal recommender systems often rely on predefined plans or collaborative filtering techniques, limiting their adaptability and personalization. This study presents a generative AI-based Meal Recommender System utilizing Variational Autoencoders (VAEs) to generate personalized and nutritionally balanced meal plans. The system processes user inputs, such as dietary preferences, nutritional goals, and ingredient availability, to provide tailored recommendations. VAEs effectively uncover hidden dietary patterns and nutritional relationships within complex data, facilitating relevant and personalized meal suggestions. The system is trained and evaluated using two integrated datasets: one containing detailed nutritional information for complete meal plans, including attributes such as calories, protein, fats, carbohydrates, and sodium, and another listing individual dishes along with their names and user ratings. The meal plan dataset connects multiple dishes into structured daily meal schedules, while the dish dataset provides popularity and quality insights through user feedback. Together, these datasets enable the generation of personalized and nutritionally optimized meal recommendations. Experimental evaluation indicates strong ranking performance with a Normalized Discounted Cumulative Gain (NDCG) score of 0.963. However, Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE) scores of 47.77, 2282.32, and 36.28, respectively, highlight potential areas for improving nutritional accuracy. A practical comparison with existing meal recommendation applications demonstrates the VAE model's advantages in terms of personalization, nutritional fine-tuning, and recommendation diversity. The research contributes to AI-driven nutrition planning, healthcare, and fitness, offering a scalable and intelligent solution for personalized dietary recommendations.

Keywords— Meal Recommender System, Generative AI, Variational Autoencoders, Nutrition Planning, Personalized Diet, Artificial Intelligence

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1. INTRODUCTION

On this day and age, people are taking care of their health and lifestyle. As people learn more about a healthy lifestyle, they try to keep away from junk food and exercise regularly. Although these are key moves toward better health, they are not enough on their own. A key factor in maintaining good health is nutrition, which will essentially determine his physical, mental and emotional health. A healthy diet can help you maintain a healthy weight and reduce the risks of chronic diseases such as diabetes, heart disease and some types of cancer. Moreover, good nutrition strengthens the immune system, enhances mental health, and boosts cognitive performance, thereby enabling people to lead productive and fulfilling lives.

Despite its importance, making sure to get the right nutrition is a major difficulty for many people. Busy lifestyles often leave people with little time to prepare balanced meals, leading them to rely on fast food or pre-packaged meals that are often high in calories but low in nutritional value [1]. According to [2], [3] limited nutritional knowledge and insight can make it difficult to manage dietary preferences, restrictions, and adhere to nutritional guidelines [4]. Without proper support, it becomes challenging for individuals to make food choices that align with their health goals.

These challenges are being addressed by recommender systems and, specifically, those that utilize generative artificial intelligence (AI). According to [5], [6], by analysing user data, including dietary preferences, fitness goals, and available ingredients, these systems can offer personalized meal recommendations. For instance, a gym person looking for a high protein dinner can get suggestions based on his nutritional requirements along with their preferences. By filtering relevant options and minimizing cognitive load, these systems simplify decision-making and provide users with intelligent support. Thus, they empower individuals to make healthier dietary decisions without necessitating a complete overhaul of their eating habits, as emphasized by [6], [7].

This research article proposes a novel personalized dietary planning framework by developing a generative AI-based Meal Recommender System utilizing Variational Autoencoders (VAEs). VAEs are chosen due to their ability to effectively capture complex and hidden nutritional relationships in meal data, making them highly suitable for personalized dietary planning. Recent studies demonstrate the global effectiveness of VAE-based recommendation systems, such as the work by [8] ,where a VAE-driven nutritional recommender achieved high accuracy (NDCG = 0.95) across diverse populations.

To ensure the proposed model generates accurate and reliable recommendations, this system will be evaluated using performance metrics such as Normalized Discounted Cumulative Gain (NDCG), Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE). These metrics are commonly applied in recommender system evaluation and will allow us to assess both the ranking quality and predictive accuracy of the generated meal suggestions.

By integrating these techniques, the proposed system seeks to provide context-aware, goal-driven meal recommendations that adapt to user behaviour over time. Through this VAE-based recommender system, the goal is to bridge the gap between nutritional requirements, dietary preferences, and practical meal planning [4]. This system aims to empower individuals to sustain balanced dietary habits effectively over the long term.

2. LITERATURE REVIEW

2.1 Overview of Recommender System

Intelligent technologies designed to manage massive amounts of data and offer customized recommendations enable effective tackling of information overload issues via recommender systems. The recommender system analyses the data to understand user’s needs, preferences and behaviour [4]. By understanding the input data, the system will provide suggestions tailored to individual users, making finding relevant information easier. Based on user actions, preferences, and surrounding components, these systems predict and suggest objects that meet certain needs and want. Applied generally in numerous sectors, including entertainment, e-commerce, and healthcare, they are crucial in improving consumer experience and involvement by way of more conveniently available and actionable information. Content-based filtering (CB), Collaborative Filtering (CF), and Hybrid Filtering (HB) approaches often utilized to meet this goal, each offering unique advantages in identifying patterns and generating effective recommendations [9], [10].

Food recommendation systems are dependent on solutions to world health problems and inadequate nutrition [11]. Research shows that such poor eating habits explain the incidence of non-contagious diseases such as diabetes, overweightness, heart ailments, and so on [12]. They can help people eat healthily by suggesting healthier alternatives, balanced meals, or portion-controlled diets [13]. It benefits these users as well as society. These systems carry extra components like nutrition recommendations and personal preferences, which help modify eating habits to reduce possible risks from inadequate nutrition[13], [14]. For example, modified meal plans provided by systems such as iDietScoreTM to specific groups, such as athletes ensure maximum performance and recuperation [2], [7]. Their food requirements and training cycles direct these efforts.

Further increased capacity of AI and machine learning is their combined application in recommendation systems. AI enables these systems to be smarter and more adaptive [14], [15]. Using advanced algorithms, such as GANs and VAEs, recommendation systems can make predictions even when little user data is available. Customized recommendations are produced even in sparse or novel data contexts using modern approaches, including GANs and VAEs. These technologies are quite useful in food recommendation systems and healthcare, where personal needs sometimes call for exact and adaptable solutions. Meal planners driven by AI, for example, might suggest dishes depending on available ingredients, dietary restrictions, and nutritional goals, thereby providing a wonderful and speedy user experience [14].

AI-powered solutions for the healthcare sector project health outcomes, offer preventive care and optimize treatment plans [14]. These systems enable people to take a more proactive approach toward better living by amalgamating real-time data from wearable gadgets, electronic health records, and other sources. In addition, their support of a better knowledge of the link between nutrition and health helps to promote long-term wellness and quality of life [3], [8].

Despite their promise, food and healthcare recommender systems face problems, including data privacy, ethical concerns, and big databases[15].While considering users' privacy, the primary concern is making the recommendations accurate and reliable. Besides that, it remains quite challenging to design systems that could allow multiple populations with varying nutritional needs. Dealing with these challenges requires constant innovation and collaboration among legislators, medical professionals, and engineers, among other sectors [7], [9].

The influence of recommender systems on food and healthcare should expand along with their development. These technologies improve personal well-being and support broader public health initiatives by providing tailored fact-based insights. Their importance as basic tools in contemporary society is demonstrated by their help in advancing improved food options and preventative healthcare [3], [6].

2.2 Recommender System Techniques

Recommender systems are the vital weapons of personalization that can predict an individual's preferences based on interaction data. They have a wide variety of applications, such as in e-commerce, entertainment, healthcare, and in fields where personalized recommendations would support decisions, improve interactions, and even enhance happiness. They have evolved from traditional CB, CF, to HB, Semantic Filtering, and Graph-Based Filtering and have advanced to modern generative AI techniques, including VAEs and GANs.

Traditional recommender systems provide recommendations either from user interaction data or item metadata. CB: Item attributes help one to suggest objects like those prior interactions with. CF identifies user-item interaction trends by item associations or user similarity [4]. Hybrid filtering helps combine different methods to solve restrictions and raise accuracy. While effective, traditional methods have a lot of significant problems [16]. Data sparsity caused by limited interaction data results in erroneous predictions. The cold-start problem is caused by a lack of data for new users or objects [4], [17], [18]. In addition, traditional algorithms can offer repetitive recommendations, hence limiting diversity and failing to expose customers to new ideas.

Two advanced methods that overcome these restrictions are Graph-based Filtering and Semantic-based Filtering. Through contextual knowledge, like ontologies or knowledge graphs, semantic filtering can show deeper connections between things, thus allowing more important recommendations. Graph-Based Filtering finds indirect linkages and complex interconnections that improve accuracy and diversity using user-item interactions as a graph [19].

Combining a new generative model using the AI system will give a different perspective on working with recommenders. Unlike traditional methods, which rely heavily on past data, ranging from generative models, they can still work better on data sparsity and unforeseen events. GANs build up quality using a discriminator and produce synthetic data from a generator [20]. For example, GANs can make personalized meal suggestions based on dietary preferences, availability of ingredients, and nutrition goals. VAEs, on the other hand, are deep models that uncover latent patterns for making probabilistic recommendations by compressing user-item interactions into a continuous latent space [21]. These models provide the influx of creativity that suits the best fit into the user's palate and seem especially effective in scarce environments. Together, GANs and VAEs can be dynamically tuned for user preferences and broaden the scope of recommender systems.

The evolution of recommender systems unravels the benefits and shortcomings of both generative and traditional approaches. Conventional methods provide a consistent basis for generating correct and interpretable recommendations, especially when the user preferences are well-defined, and the data is rich.

2.3 Generative AI Techniques

Generative AI, such as VAEs and GANs has dramatically expanded the scope of creativity and personalization in many areas, which has revolutionized several fields [18], [22], [23]. In recommendation systems, such advanced methods have provided solutions to the suitable room challenges that such systems have suffered the cold-start, lack of data, or even over-specialization. In particular, the ability of VAEs as well as GANs, among others, has greatly altered some recommender systems by fixing some of the problems they encountered such as cold-start phenomenon and overspecialization. These new models enabled the generation of diverse, relevant, and individual recommendations that were impossible before [24], [25].

2.3.1 Generative Adversarial Networks (GANs)

GANs are a generative model that utilizes neural networks to learn and approximate arbitrary probability distributions. Through adversarial training, GANs synthesis reasonable user-item interactions to solve problems in recommendation systems. This process involves two key components: the generator and the discriminator [26]. The generator is responsible for creating synthetic user-item interaction data that resembles real interactions, while the discriminator evaluates whether the generated data is authentic or fabricated, thereby guiding the generator to improve its outputs over time [25].

GANs have been great for bringing diversity in recommending products and dealing with cold-start issue situations. It can generate personalized recommendations with minimal input data because it can simulate realistic interaction scenarios [27], [28]. However, there are several challenges that GANs have experienced, including mode collapse and training instability. Such problems might cause repeated outputs as a result of insufficiently diverse data points generated by the generator. These challenges emphasize careful hyperparameter tuning and strong optimization techniques that guarantee performance consistency and reliability [24], [27].

Building upon these foundations, [8] introduced FoodRecGAN, a generative adversarial network specifically designed for food recommendation tasks. FoodRecGAN models user preferences and dietary patterns to generate personalized meal suggestions. By utilizing adversarial learning, the system is able to refine its recommendations based on user feedback, thereby enhancing recommendation diversity and relevance over time. Their results demonstrated significant improvements in recommendation accuracy compared to traditional collaborative filtering methods, emphasizing the potential of GANs in addressing personalized nutrition challenges [8].

GANs have been a powerful mechanism in enhancing recommendation systems by enabling the creation of personalized, realistic, and diverse content [29]. Despite being confronted with training instability and mode collapse, recent advancements, like FoodRecGAN, demonstrate that adversarial learning models can significantly improve recommendation quality by capturing fine-grained user preferences.

With continuous progress in GAN architectures in the form of incorporating context-awareness, conditional generation, and merging these with other approaches, GAN-based models offer promising avenues to overcome the constraints of traditional recommender systems such as data sparsity, cold-start problems, and overspecialization. The use of GAN-based models in food recommendation tasks is a testament to their important role in advancing personalized nutrition planning and dynamic meal recommendation systems.

2.3.2 Variational Autoencoders (VAEs)

VAEs are probabilistic generative models for finding latent relationships by encoding user-item interaction in an easily reduced latent space, and keep that information limited to basic context. They transform raw user interaction data using an encoder-decoder framework into latent variables and decode those latent variables to reshape the original interactions. This capability enables VAEs to generate realistic and personalized outputs even in the presence of sparse or incomplete data, a common challenge in traditional recommendation systems. With that phenomenal capacity, VAEs surpass the difficulties of sparse-data conventional recommenders and can be applied flexibly to several datasets [27].

VAEs are indeed adaptably practical. They recommend niche products to consumers in e-commerce who have little to no interactions prior. VAEs also help in preparing personalized meal plans based on dietary restrictions or available items in their storage. Due to such features, they work very well in data-scarce conditions [27].

Moreover, VAEs introduce a structured method for sampling user preferences, enabling the generation of diverse recommendations that are not solely bound by historical behaviour. This property ensures that recommendation models using VAEs can suggest novel and favourable options, enhancing user satisfaction and engagement.

This has its limitations, however. The probabilistic models are computationally intensive, as they require relatively high computation resources to train and infer. Training VAEs often involves tuning complex hyperparameters like the Kullback-Leibler (KL) divergence weight to balance reconstruction quality and latent space regularization, which can complicate optimization. Furthermore, the abstract nature of latent variables diminishes interpretability, which is a vital requirement in disciplines such as healthcare, where openness and trust are paramount [24].

Recent advancements have sought to address these challenges by integrating attention mechanisms into VAEs to improve feature learning and by proposing conditional VAEs (CVAEs) to better control the generation process. For example, [30] successfully employed a VAE-based model combined with ChatGPT to generate personalized, nutritionally accurate meal plans, highlighting the effectiveness of VAEs in personalized dietary recommendation systems.

These innovations reinforce that VAEs remain a powerful and evolving tool in recommender system development, particularly for applications demanding personalization, diversity, and adaptability to sparse or incomplete data scenarios.

2.3.3 Comparison of Generative AI frameworks

Methods such as GANs and VAEs have proven particularly useful for mitigating the cold-start issue and working with sparse datasets. From the design viewpoint, GANs introduce diversity and creativity by reproducing real-life user-item interactions. In contrast, VAEs are effective when working with big data sets and are structured in the form of latent space encoders. These trends are relevant in industries starting from entertainment and ending with healthcare [24], [27].

Each method, however, has its downsides. First, VAEs are highly scalable and easy to use. However, the hidden variables are almost entirely opaque. This could translate to low levels of trust by the users. Meanwhile, GANs are resource-intensive and prone to mode collapse. Therefore, with a low tractable regime, they become hard to implement. All these methods have very complex optimization processes necessary for achieving reliability and efficiency.

Generative models such as VAEs and GANs have great potential for developing personalization in recommendation systems but also face limitations. In the future, more efficient hybridization will increase the efficiency for VAEs and GANs, making them integrated parts of recommendation systems. When combined with other methods, they have the potential to greatly improve the performance of these systems, enabling more personalized and unique recommendations to be made. More research is still needed on the computing requirements of all these mentioned and upcoming technologies in enterprises.

2.4 Summary of Recommender System Techniques

Recommendation systems employ diverse filtering methods, which, with their use cases, could fit particular user requirements. All strategies have their limitations, even if they are able to address issues of up-scaling, user satisfaction, and the accuracy of the recommendations. These strategies are summarized on Table 1 with their advantages and limitation.

Table 1. The Advantages and Limitations of Recommender Techniques

Technique	Advantages	Limitations
GANs	- Create new and diverse recommendations - Solve cold-start and data gaps - Suggest fresh options beyond user history	- Hard to train (unstable sometimes) - Need careful tuning - Hard to explain why it recommends something
VAEs	- Work well with little or missing data - Make personalized and varied suggestions - Capture hidden patterns in user needs	- Take a lot of computing power - Results are harder to interpret - Need balance when training

Meal recommender systems are a great fit for generative AI methods such as VAEs and GANs since they can solve important issues, including data sparsity, cold-start concerns, and the demand for diverse, customized recommendations. These models improve diversity and personalising by constantly adjusting to user choices and producing creative meal alternatives that fit dietary restrictions, such as vegan, gluten-free, or high-protein diets. Generative AI is a useful technique for contemporary applications in personalised nutrition and meal planning since it offers overall dynamic, adaptive, and highly customised meal recommendations.

2.5 Related Works

In recent years, generative AI techniques have demonstrated significant potential in improving meal recommender systems by addressing critical issues such as personalization, nutritional accuracy, and diversity in meal planning. In 2020, [31] introduced a VAE framework explicitly designed for recognizing food ingredients directly from images, effectively bridging textual and visual data domains. The key finding of this work was its superior alignment capability of multi-modal data representations using Wasserstein distance [32]. This method surpassed previous state-of-the-art models, notably achieving an impressive F1-score of up to 50.05 on the Recipe1M dataset. This advancement closely aligns with our study by highlighting VAEs efficiency in managing and integrating complex food-related multi-modal data, a critical aspect for generating precise and personalized meal recommendations based on nutritional and ingredient-based profiles.

Besides that, [33] developed RECipe, a new multi-modal recipe recommendation system using knowledge graph embedding guided VAE (KG-VAE). The recommendation approaches employed behavior-, review-, and image-based recommendations through understanding structured knowledge graphs. Their major findings included cost-effective and important improvements on ranking effectiveness, which has been computed by Hit Rate (HR) and NDCG. These findings demonstrate the effectiveness of combining structured data with generative models and learned application-related insights to further advance measure improvement of recommendations. This directly informs our research since it would show how structured information integrated with generative AI would improve the quality of personalized meal planning and recommendations.

In 2024, [34] developing NutrifyAI, a sophisticated system integrating real-time food detection, nutritional analysis, and personalized meal suggestions. Utilizing advanced computer vision techniques such as YOLOv8 and leveraging external nutritional data APIs, the system achieved precision (78.5%), recall (72.8%), F1-score (75.5%), and overall accuracy (75.4%), highlight the model’s efficacy in real-time scenarios. A critical insight from this research was its potential for real-time adaptability and immediate dietary feedback, directly impacting user engagement and dietary adherence. This aligns closely with our objectives by emphasizing the critical role of accurate nutritional data and real-time user interactions to enable dynamic and responsive meal recommender systems.

In the same year, [35] proposed a groundbreaking nutrition recommendation approach that combined the deep generative capabilities of VAEs with the conversational proficiency of ChatGPT. Their proposed system effectively generated personalized meal plans tailored explicitly to detailed dietary profiles, achieving exceptional macronutrient accuracy levels of 87%. A notable finding of this study was how the integration of conversational AI significantly enriched the diversity and adaptability of generated meal plans, making them more appealing and engaging to users. This method validates and reinforces the core concept of our study by highlighting how deep generative models can effectively combine nutritional precision with engaging, diverse meal recommendations.

Additionally, [36], introduced a novel generative AI framework specifically for personalized inpatient meal planning. Their approach, applying cutting-edge models such as GPT-4 and DALL-E [37], carefully incorporated patient-specific data like that from Electronic Health Records (EHRs) and strictly adhered to professional nutritional guidelines. The system generated detailed textual and visual meal plans, providing a notable increment in patient satisfaction and dietary adherence. This research speaks to our study, emphasizing the need to blend expert-driven nutritional guidelines with strong generative AI methodologies to deliver precise, personalized, and clinically pertinent meal planning.

These important milestones together form a strong theoretical and applied basis for our research and indicate clearly how generative AI methods, particularly VAEs and GANs, can solve very critical problems with regard to nutritional accuracy and personalization in also time-sensitive meal recommendation systems.

2.6 Summary of Related Works

An overview of prior research on meal recommender systems is presented in Table 2, which offers insights into current methods and research directions.

Table 2. Key Aspects and Findings of The Research

Article	Paper Title	Key Findings	Evaluation Metrics	Datasets
[31]	A Cross-Modal Variational Framework for Food Image Analysis	The authors developed a VAEs framework for ingredient recognition. Using datasets like Yummly-28K, the system improved multi-modal data alignment in food analysis.	The framework's performance was assessed using the F1-score and Intersection over Union. The Yummly-28K dataset achieved an F1-score of 46.54 and an Intersection over Union (IoU) of 32.25. On the Recipe1M dataset, it reached an F1-score of 50.05 and an (IoU) of 33.38. These results outperformed state-of-the-art models for ingredient recognition, demonstrating robustness and adaptability.	Yummly-28K and Recipe1M
[33]	RECipe: A Multi-Modal Recipe Knowledge Graph	The authors introduced a multi-modal recipe framework integrating behavior, reviews, and images with knowledge graph embedding models, improving ranking metrics	The evaluation utilized the Hit Rate, NDCG, Mean Reciprocal Rank, and Mean Rank to measure ranking effectiveness. The framework showed significant improvements in ranking tasks across behavior-based, review-	Kaggle (Food.com and Allrecipes)

		and enabling zero-shot recommendations.	based, and image-based recommendations, demonstrating its capability to integrate diverse modalities.	
[34]	NutrifyAI: An AI-Powered System for Real-Time Food Detection, Nutritional Analysis, and Personalized Meal Recommendations	The authors introduced NutrifyAI, a real-time system integrating food detection (YOLOv8), nutritional analysis (Edamam API), and personalized meal recommendations. The system achieved high recognition accuracy and supported dietary planning via an interactive mobile and web interface.	NutrifyAI achieved a precision of 78.5%, recall of 72.8%, and an F1-score of 75.5%, with an overall accuracy of 75.4% when tested on the Food Recognition 2022 dataset. The system demonstrated efficient real-time capabilities, with an average detection time of 1.5 seconds per image.	Github-Food-Recognition
[35]	AI Nutrition Recommendation Using a Deep Generative Model and ChatGPT	The authors integrated VAEs with ChatGPT for building personalized meal recipes and were able to get good satisfaction concerning nutrient content and meal diversity, suitable for meal personalization.	The accuracy of macronutrient distribution was assessed, achieving over 87% accuracy for virtual user profiles and 84.19% for real user profiles. These metrics validated the system's ability to generate highly accurate, personalized meal plans that align with nutritional guidelines while ensuring diversity through ChatGPT generated meal recommendations.	Zenodo & IEEE
[36]	Personalized Meal Planning in Inpatient Clinical Dietetics	The authors introduced a dual generative AI system for personalized meal plan formulation in clinical settings. It applied custom patient data to alter and illustrate meals, emphasising clinical relevance and user endorsement.	The evaluation metrics used were the degree to which the patients and the level of satisfaction of the patients have respected dietary restrictions. The system was constantly refined through collaboration and communication loops, and the text and visual meal plans were readily improved to suit changing requirements of the patients.	Not publicly available

3. RESEARCH METHODOLOGY

3.1 Outline of Research Methodology

This section gives a clear and structured approach to designing and developing a generative AI-based meal recommendation system with the aim of producing a model promising accuracy and efficiency from the user's perspective by suggesting a balanced meal customized for the individual. The research follows a stepwise approach, beginning with the identification of the problem and gathering and preprocessing data, selecting the appropriate AI model, building up the system itself, and finally, evaluating and analyzing the model's performance. Each stage is diligently engineered to respond to the research objectives and guarantee satisfaction along the dimensions of their implementation. Figure 1 outlines the process of this research methodology.

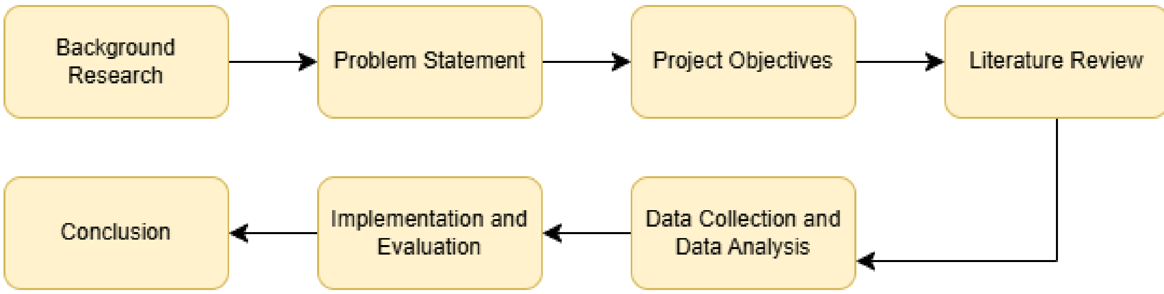

Figure 1. Flow of Research Methodology

As shown in Figure 1, the research process includes seven major phases that guide the operation of the step-by-step flow of the methodology. Each of these phases have a relationship with the other, and they come together to make sure that the entire process is cohesive and stable. The methodology is designed to address the challenges identified in the problem statement, such as selecting the most suitable generative AI techniques, optimizing system performance, and integrating nutritional data into the recommendation process.

3.2 Dataset and data dictionary

The data for this project has been taken from the Kaggle Meal Plan Search Dataset, which contains comprehensive meal plans and individual dishes. The dataset includes two key components, *mealplans.csv* and *dishes.csv*, which are stored in the files. The meal plans dataset has records of many meal plans, which include macronutrient and micronutrient values, together with references to the individual dishes that make up the meal plan. The names of the meals and the user ratings are included in the *dishes.csv* dataset.

In the *mealplans.csv* file contains some info on nutrition values of meal plans like total calories, macronutrient intake (proteins, fats, carbs), vitamins, minerals, and so on. The file also includes references for each of the individual dishes, categorized by meals into breakfast, lunch, dinner, and snacks. The details and data types of the attributes in this file are shown in Table 3.

Table 3. Attributes Descriptions of the Meal Plans Dataset

Attribute Name	Details	Field Type
id	Unique identifier for each meal plan	int64
calories	Total caloric content of the meal plan	float64
caloriesFromFat	Calories derived from fat	float64
totalFat	Total fat content in grams	float64
saturatedFat	Saturated fat content in grams	float64
cholesterol	Cholesterol content in milligrams	float64
sodium	Sodium content in milligrams	float64
potassium	Potassium content in milligrams	float64
totalCarbohydrates	Total carbohydrate content in grams	float64
dietaryFiber	Dietary fiber content in grams	float64
protein	Protein content in grams	float64
sugars	Total sugar content in grams	float64
vitaminA	Vitamin A content in IU	float64
vitaminC	Vitamin C content in milligrams	float64

calcium	Calcium content in milligrams	float64
iron	Iron content in milligrams	float64
thiamin	Thiamin (Vitamin B1) content in milligrams	float64
niacin	Niacin (Vitamin B3) content in milligrams	float64
vitaminB6	Vitamin B6 content in milligrams	float64
magnesium	Magnesium content in milligrams	float64
folate	Folate content in micrograms	float64
breakfast0 - breakfast2	IDs of dishes included in breakfast	int64
lunch0 - lunch4	IDs of dishes included in lunch	int64
dinner0 - dinner6	IDs of dishes included in dinner	int64
snacks0 - snacks1	IDs of dishes included in snacks	int64
id	Unique identifier for each meal plan	int64
calories	Total caloric content of the meal plan	float64
caloriesFromFat	Calories derived from fat	float64
totalFat	Total fat content in grams	float64
saturatedFat	Saturated fat content in grams	float64
cholesterol	Cholesterol content in milligrams	float64
sodium	Sodium content in milligrams	float64
potassium	Potassium content in milligrams	float64
totalCarbohydrates	Total carbohydrate content in grams	float64
dietaryFiber	Dietary fiber content in grams	float64
protein	Protein content in grams	float64
sugars	Total sugar content in grams	float64
vitaminA	Vitamin A content in IU	float64
vitaminC	Vitamin C content in milligrams	float64
calcium	Calcium content in milligrams	float64
iron	Iron content in milligrams	float64
thiamin	Thiamin (Vitamin B1) content in milligrams	float64
niacin	Niacin (Vitamin B3) content in milligrams	float64
vitaminB6	Vitamin B6 content in milligrams	float64
magnesium	Magnesium content in milligrams	float64
folate	Folate content in micrograms	float64
breakfast0 - breakfast2	IDs of dishes included in breakfast	int64
lunch0 - lunch4	IDs of dishes included in lunch	int64
dinner0 - dinner6	IDs of dishes included in dinner	int64
snacks0 - snacks1	IDs of dishes included in snacks	int64
id	Unique identifier for each meal plan	int64

The *dish.csv* file contains a list of dishes with their respective dish id, dish name and user ratings. Just like the meal plan mealtime keys refer to the dishes, the dish ID is a single, unique identification for each dish, tying it to a meal plan. From user ratings, the system can form a recommendation process that takes into account the popularity of the dishes. The attribute details and data types for the *dishes.csv* dataset are outlined in Table 4. Table 4 describes the attributes of the *dishes.csv* dataset, which includes dish titles and user ratings for ranking meal popularity.

Table 4. Attributes Descriptions of the Dishes Dataset

Attribute Name	Details	Field Type
id	Unique identifier for each dish	int64
title	Name of the dish	string
rating	User rating of the dish	float64

3.3 Variational Autoencoders (VAEs)

VAEs proposed by [38] embed the input into a probabilistic latent space to generate diverse and meaningful outputs of the model. It generally consists of an encoder that represents input data probabilistically in the latent space and a decoder that reconstructs the data by using this representation. Compared to normal autoencoders, a VAE applies a probabilistic framework that outputs generated data by merely sampling on the latent space, which is perfect for tasks in which variety and adaptability matter, like in personalized recommendations.

Fundamentally, VAEs optimize a mathematical quantity known as the Evidence Lower Bound (ELBO), which balances two objectives reconstruction loss and the KL divergence loss [39] . The ELBO is expressed from Equation. The ELBO is expressed from Equation (1).

$$L(x;\theta,\phi) = Eq\phi(z \mid x)[logp\theta(x \mid z)] - KL\big(q\phi(z \mid x) \parallel p(z)\big) \tag{1}$$

The ELBO includes two key parts:

- The reconstruction loss ensures that the output closely matches the input.
- The KL-divergence term ensures the latent distribution remains close to a standard prior distribution.

The reconstruction loss measures how well the decoded output matches the original input. It encourages the decoder to generate outputs that are accurate reconstructions of the inputs. This loss can be computed using Binary Cross-Entropy (BCE) or MSE, depending on the data type. The formula for reconstruction loss using MSE is expressed. It is computed as presented in the following Equation (2).

$$\text{Reconstruction Loss} = |x - \hat{x}|^2 \tag{2}$$

The KL divergence loss regularizes the latent space by making the approximate posterior distribution $q(z|x)$ close to the prior $p(z)$, typically assumed to be a standard Gaussian $\mathcal{N}(0,I)$ The KL divergence term is computed as the Equation (3).

$$\text{KL Divergence Loss} = -\frac{1}{2}\sum_{i=1}^{d}(1 + \log(\sigma_i^2) - \mu_i^2 - \sigma_i^2) \tag{3}$$

By minimizing the total loss, the VAE learns to encode meaningful representations and generate realistic reconstructions. Sampling from the learned latent space enables VAEs to generate new data records, making them valuable for recommender systems. In recommender systems, VAEs can manage multi-criteria data by extracting user preferences and interactions.

The VAE model first encodes user-item interaction matrices into a latent space through an encoder network, generating latent variables. he decoder then reconstructs the interaction matrix from these latent variables, predicting missing values by capturing patterns in user behaviour.

The VAE model effectively handles data sparsity by mapping incomplete user-item matrices into a dense latent representation, inferring missing interactions based on learned correlations. The KL divergence term ensures that the latent space is smooth and continuous, making it easier to sample plausible missing values. In multi-criteria recommendation settings, VAEs can leverage relationships across different rating aspects to improve imputation quality.

Overall, VAEs combine the benefits of traditional autoencoders (compact representation learning) with probabilistic modelling (uncertainty handling and generative capabilities). Their ability to generalize from sparse or incomplete data makes them a robust choice for real-world personalized meal planning and nutrition recommendation systems.

3.4 Evaluation metrics

To assess the performance of the VAE-based meal recommender system, several evaluation metrics are employed. These include NDCG, RMSE, and MAE. Each metric provides insight into the system's ability to deliver accurate, relevant, and personalized meal recommendations.

3.4.1 NDCG

NDCG is a metric commonly used to evaluate the quality of rankings, especially in search engines and recommendation systems. It measures how well a system ranks items based on their relevance to a specific query or user. The primary goal of NDCG is to prioritize highly relevant items appearing earlier in the ranking, as these items are considered more beneficial to the user. The formula for DCG at a particular rank p is given as in Equation (4).

$$DCG = \sum_{i=1}^{p} \frac{rel_i}{\log_{2(i+1)}} \tag{4}$$

Where:
- rel_i: Represents the relevance score of the item at position i.
- p: Refers to the total number of items considered for ranking.
- IDCG: Computed using the same formula as DCG but assumes an ideal ordering of items, where the most relevant items are ranked at the top.

IDCG is computed similarly but assumes an ideal ordering of items. NDCG is then defined as in Equation (5).

$$NDCGp = \frac{DCG_p}{IDCG_p} \tag{5}$$

In the context of recommendation systems, NDCG evaluates how well the system ranks items based on their relevance to the user. A higher NDCG score, closer to 1, indicates that the system's ranking aligns closely with the ideal ranking, where the most relevant items appear at the top. NDCG is especially useful when comparing the performance of various ranking algorithms or systems. This normalization helps prevent the comparison of the DCGs for queries with different numbers of relevant items from being skewed. Nevertheless, NDCG has some shortcomings, including reliance on the relevance scale, which varies for each application. NDCG is still a strong and commonly used metric for assessing the quality of the recommendation systems, followed by ranking and channelling a high-level understanding of systems capabilities to better serve the user in terms of the data that is made available to them.

3.4.2 RMSE

RMSE is a popular tool used in regression and predictive modelling to check how accurate a system's predictions are. In recommendation systems, RMSE helps measure the gap between what the system predicts (like the nutrient content of a meal) and the actual values from the user or dataset. A smaller RMSE means the predictions are more accurate, making it a trustworthy way to gauge how well the system is performing. RMSE is defined as the square root of the average of squared differences between predicted values ($\hat{y}$) and actual values as shown in Equation (6).

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \tag{6}$$

Where:

- N : The total number of predictions made by the system.
- $\hat{y}_i$: The actual value of the i-th data point.
- $\hat{y}_i$: The predicted value of the i-th data point.

RMSE is an effective measure in recommendation systems for checking the validity of predictions, specifically for meal plans or user preferences. For instance, for a meal planning recommendation system, the predicted values can be attributes like the calories, protein, fats, or sodium in a given meal recommendation. The actual values would therefore be the actual dietary requirements of the user. RMSE gives an idea of how well the recommendations are in relation to what the user requires.

To calculate RMSE, you take the difference between each predicted and actual value, square each difference, average them, and then take the square root. The process provides more weight to larger errors, so RMSE is great at picking up big gaps between prediction and actuality.

3.4.3 MAE

MAE is a straightforward metric used to evaluate the accuracy of predictions in recommendation systems. It measures the average absolute difference between predicted values ($\hat{y}$) and actual values (y). making it an intuitive way to assess system performance. The formula for MAE is given as in the Equation (7).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \tag{7}$$

MAE is a direct measure of prediction error, in the sense that it quantifies the average difference between prediction and reality without distorting big error impacts. Therefore, MAE is more outlier-robust than RMSE. When it comes to meal recommendation, MAE can quantify the level of correspondence between predicted and real values of nutrients.

3.5 Practical Deployment and Evaluation Workflow

This section provides an overview of the steps carried out in practice for implementation and validation of the VAE-based meal recommender system. The methodology begins from the exploration data analysis (EDA) stage to data preprocessing, model building, and model assessment. Figure 2 illustrates the overall workflow of the implementation process from data ingestion to evaluation.

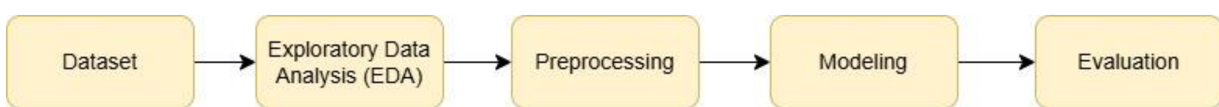

Figure 2. High-Level Workflow

Firstly, an EDA was made through the investigation of the dataset structure, relations and distribution. Visualizations including correlation matrix heatmaps, scatter plot matrices, and boxplots were utilized to explore how nutrients interact with one another, identify outliers, and identify potential problems that might impede model performance.

After EDA, it follows with data preprocessing, which aims to clean the dataset to provide high-quality inputs to the model. This included missing value handling by record deletion or imputation used, dropping duplicate rows, and scaling numeric features like calories, fats, proteins, and sodium through *StandardScaler()*. This step is to provide equal weightage to all the features during model training.

Once the data is clean and properly structured, the modelling phase begins. A VAE model was implemented using Python and the TensorFlow library. The encoder compresses input features into a latent representation and the decoder reconstructs meal plans from the latent dimension. Sampling methods were used to inject variation that increases the diversity of meal suggestions. Figure 3 shows the detailed VAE-based recommendation logic, including user preference encoding, the model training feedback loop, similarity calculation, and ranking.

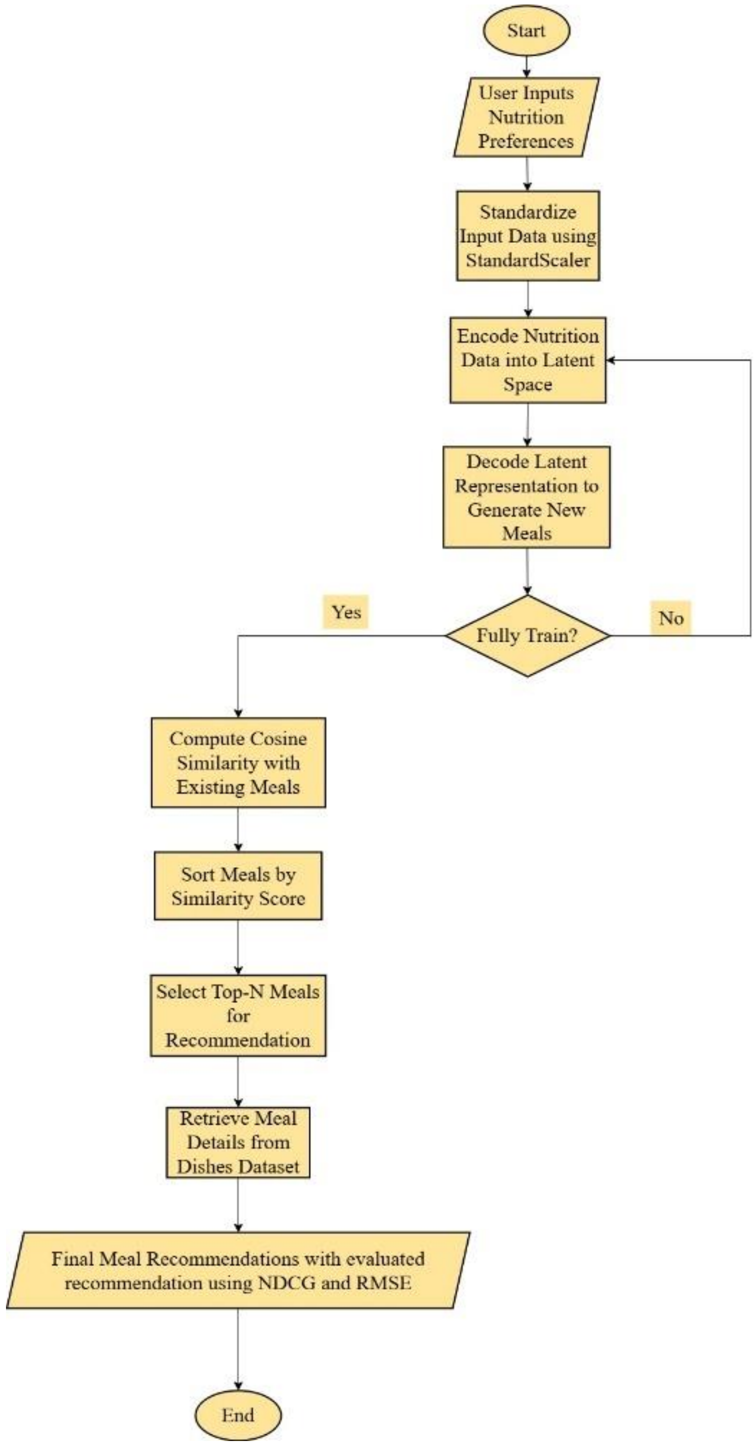

Figure 3. Flow of VAEs Based Model

Upon the completion of the VAE model training, its performance was assessed using the following key metrics: NDCG, RMSE and MAE. These measures captured salient details regarding the system's ranking accuracy and overall prediction accuracy. This end-to-end workflow captures that the developed model doesn't only comprehend the nutritional objectives but also designs precise and tailored meal suggestions to particular dietary preferences.

3.6 EDA

EDA allows for deeper engagement with the dataset, finding connections among various features, and identifying any unusual data that stand out. In this regard, we utilize three principal types of visualizations: a correlation matrix heatmap, a scatter plot matrix, and boxplots for detecting outliers.

3.6.1 Correlation Matrix Heatmap

The correlation matrix's heatmap assists in visualizing the relationships existing between the various numeric features available in the dataset. As for the axes, both X and Y represent nutritional features which are calories, fats, sodium, protein, vitamins, and minerals. The corresponding cell of each matrix displays the value of Pearson correlation coefficient (CORR) for the nutrient pair. The closer the value is to 1, the stronger the positive correlation, whereas, the closer it is to -1, the stronger the negative correlation. For example, calories and total fat exhibit a high correlation (0.86), meaning that meals higher in fat tend to have more calories. Similarly, protein is strongly correlated with niacin and vitamin B6, reflecting their common presence in high-protein foods. These insights are useful for understanding which nutrients are naturally linked and how they influence meal composition. Figure 4 illustrates the correlation matrix heatmap.

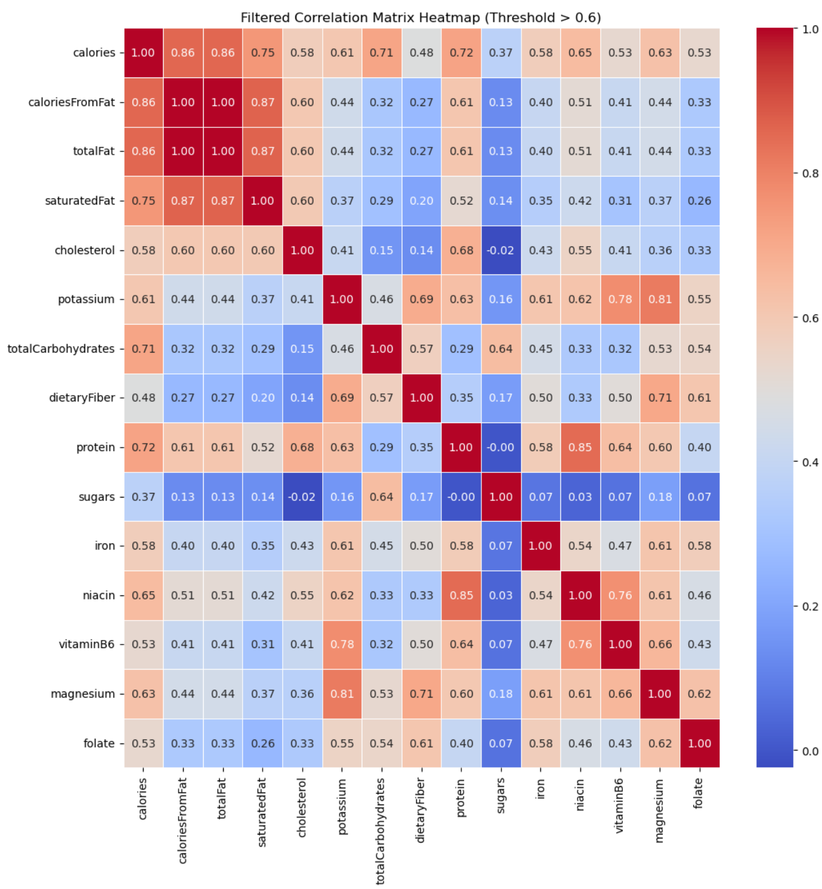

Figure 4. Correlation Matrix Heatmap

3.6.2 Scatter Plot Matrix with Density Plots

The scatter plot matrix displays the optional nutritional features like calories, caloriesFromFat, total_calories, fat, saturated fat, and cholesterol. Lower triangular matrix cells show the scatter plot of respective variables whereas diagonal plots show KDE of every feature's distribution.

Nutritional attribute value on the X and Y axis makes identification of correlation and distribution degree simple and visually pleasing. For better understanding, consider scatter plot for total_calories and fat (CORR:0.87). There is a clear linear relation, meaning growth in fat content results in greater total calories. Also, caloriesFromFat is nearly the same as totalFat (CORR:0.87), pointing that indeed fat is the main constituent of calories.

The cholesterol variable might be moderately positively correlated with both total fat and saturated fat at around 0.60, suggesting high fat meals would also be of high cholesterol. This is aligned with the field's knowledge because foods that have high amount of cholesterol contain large volume of saturated fats [40].

The KDE plots evidentially capture the silhouette of the features: both the central tendency and variance. Calories and fat features have a right-skewed distribution. This indicates that most of the meals are moderately calorically dense with a few meals that are exceedingly high. Sodium and cholesterol are also right-skewed with some extreme upper outliers which may require special treatment when dealing with outliers. Like the correlation heatmap, this figure strives to supplement and explain the structure and symmetry of the nutritional dataset and helps with feature selection for the modelling process. Moreover, it helps understand the interactions between nutrients, thus helping in designing accurate meal plans suited for individual needs. Figure 5 shows the updated scatter plot matrix and density curves.

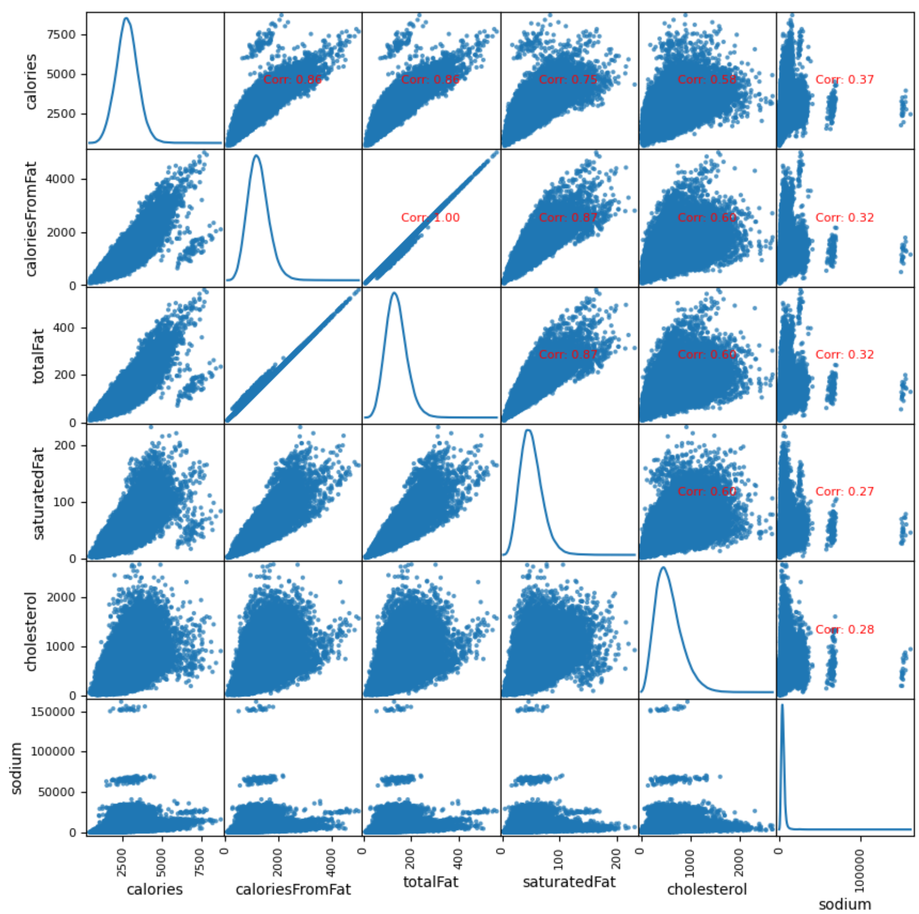

Figure 5. Scatter Plot Matrix with Density Plots

3.6.3 Boxplot for Outlier Detection

Nutritional aspects such as total fat, calories, cholesterol, and sodium are some of the issues addressed by the data set, and boxplots identify the outliers. These extreme values are marked as single points demarcated outside the whiskers in the boxplot. These extreme values may correspond to high-caloric or high-sodium meal plans that one must be cautious of to develop good recommendations. In Figure 6, the boxplot for outlier detection is depicted.

3.7 Data Cleaning

Before the dataset can be processed for model training, the initial step involves data cleaning. Data cleaning is an essential step to ensure the dataset is properly structured and optimized for model training. This step involves handling missing values, removing duplicate records, validating data formats, and standardizing nutritional values. Properly cleaned data helps improve the accuracy and efficiency of the recommendation system.

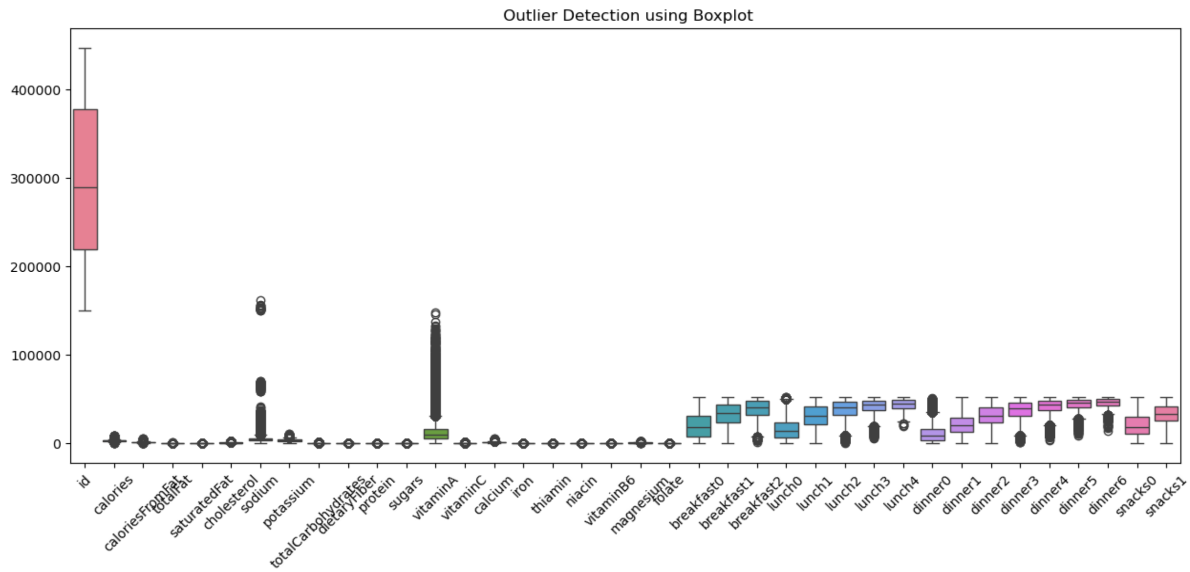

Figure 6. Boxplot for Outlier Detection

3.7.1 Handling Missing Values

The dataset is first checked for null or missing values using *.isnull().sum()*. There are some missing values in the meal recommendations, which are breakfast, lunch, dinner, and snack in the meal plan dataset. Some of the ratings for the dishes dataset are missing. To handle this missing data, we remove the column that has more than 50% of the missing data and remove the rows that have missing data for the meal plan dataset. For the *dishes* dataset, we fill in the missing ratings using the median.

3.7.2 Removing Duplicate Entries

Duplicate records will suffer the model's learning process. The dataset is checked for duplicate meal plans or dishes using *.duplicated().sum()*. There is no duplicated data in the dataset.

3.7.3 Standardizing Nutritional Features

Standardize all the numerical values of the features such as calories, proteins, fats, and sodium using *StandardScaler()* in order to equate their scales. In this step, we make sure that each feature is scaled so that no one feature experiences undue influence on the recommendation system. All the features are put on an equal footing to contribute to the outcome. In general, data cleaning consists of handling missing values, duplicates, dish reference checks, and feature scaling to make the dataset accurate and consistent for training models. In that respect, the system can do better and provide more personalized recommendations of meals. These moves are necessary because they avail some modeling performances.

3.8 Data Modeling

The research development of the phrase of generative AI Based meal recommender system use VAE to create personalized meal recommendations. The training begins with the standardization of nutritional data from meal plans. This is to ensure all data is on a uniform scale.

The VAE model comprises two major components: the encoder and the decoder. As illustrated in Figure 6 and Figure 7, it shows the detailed encoder and decoder code structures, respectively. The encoder is responsible for compressing detailed nutritional meal data into a simplified, lower-dimensional representation known as the latent space. This latent representation captures underlying patterns and relationships between various nutritional features, facilitating more accurate and diverse meal recommendations. Figure 7 provides a detailed illustration of the encoder's code structure, showing the systematic transformation of nutritional input features into the latent space.

```
# Encoder
inputs = Input(shape=(original_dim,))
x = Dense(128, activation='relu')(inputs)
x = Dense(64, activation='relu')(x)
z_mean = Dense(latent_dim)(x)
z_log_var = Dense(latent_dim)(x)
z = Lambda(sampling)([z_mean, z_log_var])
encoder = Model(inputs, [z_mean, z_log_var, z], name="encoder")
```

Figure 7. Encoder Architecture

Next, the decoder takes this simplified latent representation and reconstructs it into detailed nutritional information, resulting in realistic and varied meal suggestions. This ensures the generated meals align closely with user dietary needs and preferences. Figure 8 depicts the decoder's code structure, illustrating how latent variables are expanded and transformed back into detailed meal nutritional attributes.

```
# Decoder
latent_inputs = Input(shape=(latent_dim,))
x = Dense(64, activation='relu')(latent_inputs)
x = Dense(128, activation='relu')(x)
outputs = Dense(original_dim, activation='linear')(x)  # Use linear activation
decoder = Model(latent_inputs, outputs, name="decoder")
```

Figure 8. Decoder Architecture

The essential point of such a model is the choice of the latent space dimension and has been set to 8. This is a balance point between the prediction of nutrition diversity without making the model cumbersome. If dimension numbers are low, it will lack diversity, and if too much, they will all have extremely similar meal suggestions that do not possess high novelty. For the purpose of increasing diversity in suggestions, the model incorporates a sampling function within it to add controlled randomness to the latent space. With this low variance, users receive a broader set of appealing and personalized meal choices.

VAE trains itself by alternating reconstruction loss and Kullback-Leibler (KL) divergence while training. It thus enables the model to generate accurate, varied, and relevant meal suggestions. Generated meals are compared against the user-specified nutritional preferences with cosine similarity measures based on these learned embeddings, ordering meals based on relevance to the user.

Lastly, the recommender system is evaluated based on RMSE, MAE and NDCG. These measures guarantee the recommended meals by the model are properly matched with user preferences while giving an ideal combination of nutrition.

3. RESULTS AND DISCUSSIONS

The VAE meal recommender program has received preliminary results indicating it is quite efficient at constructing user-specific meal plans based on their dietary needs. The system was evaluated using several performance metrics, such as the RMSE, MAE and NDCG. These indicators determine the precision and relevance of the generated meal plans. Table 5 presents the detailed evaluation results of the VAE model.

Table 5. Evaluation Metrics for VAE-based Meal Recommender System

Evaluation Metric	Result	Interpretation
NDCG	0.9634	High relevance in ranking recommended meals according to user preferences
MAE	36.28	Moderate deviation between predicted and actual nutritional values
RMSE	47.77	Indicates slightly larger error magnitude in certain nutrient predictions
MSE	2282.32	Represents overall squared differences between predicted and actual values

The NDCG value of 0.9634 shows that the recommendation score is relevant and achieves close proximity to the nutrient preference maintained with the user. The MAE shows a score of 36.2829, suggesting that this score corresponds to the average distance of about 36 units of the potential nutritional outcome from the user-specified nutritional target. Thus, it can be inferred that although the model captures most trends, there are significant disparities in specific nutrient estimates.

Besides that, a RMSE of 47.7736 was a bit higher than MAE, showing the errors in some of the nutrient forecasts. Furthermore, the MSE value of 2282.3190 This shows how much the predicted values differ from the actual ones, helping to identify areas where the model can be improved.

This VAE-based meal recommendation model has accuracy and relevance based on the results. The refined model better aligns with user-specified nutritional targets while maintaining strong predictive performance. Further enhancements could focus on optimizing latent space dimensionalities and incorporating additional nutritional constraints to fine-tune recommendations even further.

4. LIMITATIONS AND FUTURE WORK

Although the VAE-based meal recommender framework constructed in this paper has shown some promising performance in providing personalized and nutritionally balanced meal plans, there are limitations to this study as well. First, the proposed model is based only on VAEs as the underlying generative model. While VAEs can well capture the underlying dietary patterns and mitigate data sparsity, they may lead to recommendations being less diverse or overly smoothed because of its probabilistic interpretation. This lack of creativity in the suggestions can prevent the system from producing very creative or surprising meal suggestions, that would increase user retention.

Secondly, the dataset, while large, includes only static nutritional data and pre-defined user ratings. In reality, user preferences might also be more dynamic, for example, due to seasonality, changing dietary goals or lifestyle, which is not reflected in the current tdataset.

Another limitation is with the metrics used for evaluation. NDCG, RMSE, and MAE are great at measuring quality of ranking and predictive accuracy but system effectiveness in practice would need to be confirmed by user studies and longitudinal behavioural measures of dietary adherence and satisfaction.

In future, we will investigate incorporating GANs into the recommendation pipeline. GANs, which can produce very diverse high-quality samples, provide a complementary approach to VAEs. By designing crowd-based models for GAN in next studies, we can compare VAE and GAN models directly in completion quality, recommendation diversity and robustness. This combination may contribute to more elaborate, creative and personalized meal plans.

This will also help us in enriching the dataset with a more diversified range in order to adapt the system to other cuisines and cultural dietary patterns as well as planning to incorporate real-time user feedback and dynamic user profiling in future extensions of the system. These improvements will enable the development of a personalised, adaptive, culturally sensitive, user centric meal recommender system that can better adjust to the personal health goals and lifestyle of the individual and through time.

5. CONCLUSION

This study conducted illustrates how AI can be integrated into giving more personalized meal suggestions using one’s dietary choices, nutritional objectives, and other health-related restrictions as the Generative AI-based Meal Recommender System utilizes the modern tools of AI technology. This work assessed state-of-the-art Generative AI models, particularly focusing on VAEs as they attempt to construct solutions to the major issues of meal recommendation systems. Some of these include the cold-start problem, data sparsity, and the ever-prevailing issue of personalization.

From a technical standpoint, the research systematically focused on exploratory data analysis (EDA) to understand nutrient relationships, preprocessing techniques to ensure clean and standardized data inputs, the construction and training of a Variational Autoencoder (VAE) model, and comprehensive evaluation using ranking and error-based performance metrics. As a result of extensive data processing, feature selection, and model evaluation, the system was able to recommend user specific meals which also had diversity and balance when it came to nutrition. The model’s accuracy and relevance were evaluated and confirmed by the competing measures of NDCG, RMSE, and MAE. These results were particularly insightful because they showed how well the VAE-based model performs in capturing dietary habits and recommending meals. However, model complexity, scalability, and interpretability pose a challenge to these promising outcomes and need further development.

Looking ahead, several directions for future work are proposed. Enhancements can be made by optimizing the latent space structure of the VAE, incorporating more complex dietary constraints, and integrating real-time user feedback into the system. The system's flexibility and ability to generalize will also be augmented by expanding the dataset to include more types of cuisines and cultures, as well as additional dietary and nutritional contexts.

In general, the research presented makes an important contribution towards the designs of intelligent meal planning systems that are easy to use and follow. It further impacts the emerging domain of AI and nutrition and serves useful purposes by automating the selection of nutritious foods to promote healthier eating habits.

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Zheng-Bin Ter: Data Curation, Methodology, System Implementation, Writing – Review & Editing;
Palanichamy Naveen: Project Administration, Writing – Review & Editing;
Jayapradha J: Project Administration, Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

The paper follows The Committee of Publication Ethics (COPE) guideline. No ethical issues. Synthetic data was used in the work.

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