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Research Article

Longitudinal Dietary Optimization via Multi-Horizon Time Series Forecasting of BMI with Transformer Networks and Personalized Recommendation using Collaborative Filtering with Implicit Feedback

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ABSTRACT

Long-term management of Body Mass Index (BMI) shows to be challenging for most people, mainly due to limitations in dietary compliance monitoring and the lack of personalized predictive guidance. Standard methods leave much to be desired when it comes to offering personalized, adaptable strategies aligned with our unique metabolic processes and changing preferences. To address this gap, this paper develops a new computational framework for longitudinal dietary optimization. We leverage early detection for BMI management as our system is powered by state-of-the-art machine learning algorithms that provide tailored, time-sensitive dietary recommendations for proactive BMI control.

The proposed system is composed of two key components that work interdependently with each other. Firstly, we proposed a multi horizon time series forecasting model of transformer networks. This element is crucial in this context as it allows us to model how a user timeline, given all their past nutritional data, can still behave differently given food ordering tendencies. By learning from these multi-axis sequences, the Transformer model predicts BMI at different future time points, allowing for preemptive rather than reactive dietary changes. Next we use CF) with implicit feedback to deploy an personalized food recommendation engine. This CF module treats users' past food order histories as implicit indicators of preference as a user. It then looks for patterns and similarities from user to user to identify foods which not only align with an inferred taste profile for that individual, but are also preferred by other, similar users.

A set of key inputs underpin the operation of the system, including longitudinal user data (history of BMI and food ordered logs) along with a database of foods with detailed nutritional information for each food item (e.g., calories, macronutrients, micronutrients sourced from datasets such as USDA FoodData Central). The main outputs are a multi-horizon BMI forecast and a dynamically generated optimized meal plan. This is designed based on anticipated BMI trajectory, the user-specific preferences from the CF module, and preset nutritional goals; For example, when BMI is predicted to increase, the plan would suggest lower-calorie, high-fiber foods, whereas for maintenance it would promote protein-rich foods. The system can be augmented with cautionary information, for example on excessive calories or fat content.

This work primarily focuses on a novel approach by optimizing state-of-the-art multi-horizon time series forecasting to directly personalize recommendations for longitudinal dietary optimization. Our system has enormous potential to support users in understanding how their BMI deviations from the normal range may influence future weight and to guide them with personalized food recommendations, leading to healthier patterns and long-term health drivers. This technology is an advancement in personalized nutrition driven by data..

Keywords: Longitudinal Dietary Optimization, Forecasting of BMI.

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INTRODUCTION

Background: The Imperative and Challenge of Healthy Weight Management

Having a healthy Body Mass Index (BMI) is thus a pillar of good health and one of the strongest predictors of free of any chronic diseases such as coronary heart disease, type 2 diabetes, and some cancers. The burden of overweight and obesity remains a major public health challenge worldwide, with unrelenting pressure on healthcare systems. Although a healthy weight is extremely desirable, accomplishing and maintaining a healthy weight over many years is difficult and often vexing to many people. Dietary management can be a challenge for the long term. People are overwhelmed with contradictory nutritional information, find it extremely challenging to consistently and accurately self-monitor what they eat, and must contend with dynamic changes in lifestyle, metabolism and nutritional demands over time.

General dietary recommendations, although they can be useful as a starting point, often do not take into consideration individual physiological differences, taste preferences, cultural eating habits, and specific health goals or conditions. Unsurprisingly, this one-size-fits-all approach results in various poor adherence and ultimately, quitting dietary plans. Moreover, many current dietary tools and apps are reactive in nature: tracking foods once consumed, instead of offering proactive guidance to halt unwanted weight gain or loss. We cannot have our meals and eat them too, especially without technology to guide our culinary endeavors a fact that is overshadowed by the challenge even those who might consider themselves savvy cooks have in planning meals that hit all the nutritional high notes and fad diet peaks while still being family-friendly and palatable let alone that compel us to eat something healthy in a way that makes us want to do so again tomorrow or the next week. Long-term weight management depends on predictive and adaptive personalized tools that steer users towards what the data shows to be sustainable healthy eating patterns.

PROBLEM STATEMENT: BRIDGING THE GAP WITH PREDICTIVE AND PERSONALIZED DIETARY GUIDANCE

This challenge underscores the need for intelligent systems that can manage the intricacies of longitudinal dietary adjustments given the limitations of existing methods. There is a massive lack of solutions capable of predicting an individual person's future BMI trajectory based on personalized historical data and behavioral data. In the absence of such predictive ability, dietary interventions are primarily reactionary, occurring only after weight fluctuations have already taken place. Vertical systems already have some level of personalization, but they are often shallow (user profiles are frequently hard-coded and can be as simple as demographics or occasional explicit preference elicitation that may be intrusive). To be genuinely effective, this type of system needs to dynamically learn users' preferences, ideally from their everyday usage (for example, their choice of food orders) and provide customized recommendations.

Hence, the main research problem that this study examines is how to produce a proactive, personalized, and timely dietary recommendations system based on correct predictions of future BMI trajectories. It moves people beyond rigid meal plans based on recommendations for general populations towards guidance that is contingent on an individual's predicted physiological state and learned preferences. More specifically, we need systems that can:

1. **Predict multiple future timelines for BMI:** Allowing users and possibly health coaches to see trends and make adjustments preemptively.

2. **Generate tailored food recommendations:** Based not only on nutritional goals but also personal preferences derived implicitly from behavior (e.g., previous food orders, etc.).

3. **Combine prediction and advice:** Dynamically adjusted diet Suggestions according to predicted BMI and individual nutritional limitations. The challenge of designing such a system integrated to enable effective longitudinal dietary management and BMI control is addressed in this research

Proposed Approach: An Integrated Framework for Longitudinal Dietary Optimization

In response to the aforementioned challenges, we propose a unified computational paradigm that integrates the powerful machine learning time-series forecasting and personalized recommendation methodologies. It is a flexible system based on user data, trained for predicting future BMI and providing optimized personalized dietary advice. Our approach is based on the following core components:

1. **Multi-Horizon BMI Time Series Forecasting with Transformer Networks:** Our core predictive capability is a forecasting module based on Transformer Networks. While transformers are particularly well-suited for natural language processing converting text into tokens they are also capable of identifying long-range dependencies and complex function approximations in any sequential data. We modify this framework for this task

by conditionally modeling the temporal dependencies of a user's BMI, taking users' historical BMI values and potentially correlated behavioral data (such as sequences generated from order history) as input. Importantly, the model is multi-horizon, forecasting BMI at multiple horizons, not just the next time step. Such foresight is vital for pre-active dietary management and intervention. The mechanism allows it to give weights to the importance of several past data points in predicting the future just like how humans consider past experiences when making decisions.

2. **Collaborative Filtering with Implicit Feedback for Food Recommendation:** The BMI prediction is further complemented by a recommendation engine which suggests personalized food items to the user. We use Collaborative Filtering (CF), the algorithm commonly adopted in recommendation systems, but a adjusted to work on implicit feedback. Designed to focus on potential ordering rather than rely by on an explicit user rating system, our system learns about user preferences and food items based on previous order history. This method allows lower burden on users, thus better capturing people`s real world preferences. The CF module discovers users whom share similar ordering behaviors to the target user, and uses the learned characteristics of the neighboring users to recommend food items relevant to the target user which they may not have encountered.

3. Dietary Optimization Module: The last component combines the outputs from the forecasting and recommendation modules. It uses the multi-horizon BMI predictions and the personalized food suggestions, along with detailed nutritional information for food items (from databases such as USDA FoodData Central). This module uses optimization logic or rule-based approaches to output a recommended meal plan or food list. The optimization takes into account the projected BMI trend (e.g., a preference for lower-calorie, higher-fiber foods if BMI is projected to rise above a healthy threshold) in line with user inferred preferences and nutritional adequacy.

CONTRIBUTIONS

This study makes several important contributions to health informatics, machine learning, and personalized nutrition.

Novel Use of Transformers for Multi-Horizon BMI Forecasting: We propose and assess Transformer Networks for the task of predicting individual-level BMI trajectories over multi-step time horizons in the context of informing dietary recommendations.

Food Recommendation based on Implicit Feedback: We show a realistic method for personalized food recommendation using Collaborative Filtering of implicit feedback extracted from user order history, bringing together preference learning and health goals.

Integrated Predictive Optimization Framework: The main contribution is the creation and prototype of an integrated predictive optimization framework that combines long-term health state predictions (BMI predictions) with personalized recommendations and food intake optimization logic. This all-in-one approach allows for proactive, data-informed, and super-custom dietary management.

RELATED WORK:

In order to inform effective optimization strategies, it is important to understand how long-term dietary habits and body mass index (BMI) interact with health outcomes. Longitudinal dietary patterns and their impact are analyzed in several studies. An example of this is in Dalrymple et al. followed mother-offspring dietary trajectories from preconception through mid-childhood, showing stable patterns associated with maternal characteristics and later childhood adiposity (e.g. BMI [1]). This emphasizes the period during early life, and even preconception period, a critical window for dietary interventions [1]. Such nutritional interventions, however, most of them studied only cross-sectionally. Lopes et al. examined a fruit and vegetable intervention 48 months later and found minimal weight loss predominantly related to engagement in primary care, with larger effects in subgroups with obesity [2]. Minari et al. showed, in a 12-month personalized nutritional intervention in Type 2 Diabetes patients, improved glycaemic control, markers of cardiovascular health, and BMI, with sustained effects at 15 months [3]. These studies highlight the importance of longitudinal analysis and personalized dietary management [1, 2, 3].

A major area of research is predicting future health trajectories, such as BMI. Wide-ranging forecasting initiatives like those of Foreman et al have applied models of life expectancy and mortality while taking to account risk factors such as high BMI and projecting trends for future incidence of non-communicable diseases [4] Data science techniques applied to large administrative data sets have been used to predict BMI itself, reporting higher accuracy when combining different types of data [5]. Indeed, more recently, research has acknowledged the limitations of BMI as a predictor and investigated alternative models treating height and weight as interacting variables, which might improve the accuracy of prediction of both metabolic and cardiovascular outcomes when compared with BMI

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alone [6]. These studies demonstrated both the promise and the difficulties in predicting BMI and using it for risk estimation [4, 5, 6].

Increasingly, time series analysis and forecasting techniques are being applied to health data. Chowdhury et al. utilized machine learning with time series feature engineering methods such as lag features and rolling statistics to identify people at risk of brain stroke and apply its BMI as one of the input variables [12]. Again, this highlights the usefulness of time dependent features in predictive health modelling [12].

More recent advances in deep learning techniques—especially Transformer networks—have also performed well on complex time series forecasting problems. While applied mainly in power systems event prediction [10]; their application in health is more recent. Zhu et al. designed an Edge-Based Temporal Fusion Transformer (E-TFT) for multi-horizon blood glucose prediction among Type 1 Diabetes patients, improving upon previous techniques while also being suited for deployment on wearables [7]. This demonstrates the promise of applying Transformer architectures to long-term dependencies present in physiological time series data that pertain to metabolic health, such as BMI [7, 10].

An efficient personalized recommendation systems transforms health insights into real world advice. 1. Gao et al. proposed a Bayesian personalized ranking model incorporating the principles of collaborative filtering to enhance recommendations of medical services using several user actions [17]. When applied to address data sparsity and cold-start problem in other domains, such as university libraries [8], collaborative filtering techniques are often combined with others and used in hybrid approaches to provide recommendations based on personalization. Within the scope of diet alone, artificial intelligence systems are being tailored to recommend diets that are customized by user factors such as body-mass index (BMI), health objectives, and even the desired cuisine from the region. [13]. In fact, there are automated dietary planning systems using the methods of constraint programming, which can provide personalized menus, fulfilling the specific clinical needs of patients in hospitals, as a certain form of dietary optimization [9].

AI, ML, and DL are being increasingly used in the field of nutrition. The landscape has been mapped by systematic reviews like the study by Theodore Armand TP et al., which have highlighted the principal applications of AI within personalized nutrition, dietary assessment, food recognition, and predictive modeling for disease prevention and monitoring [14]. ML is being acknowledged as a promising tool for analyzing high-dimensional nutritional datasets [14, 16] and building predictive models, to identify individuals at risk for malnutrition or obesity [15]. Such conclusions echo the profound potential for AI/ML to improve nutrition and augment dietary guidance via a data-driven, personalized manner [14, 15, 16].

It is based on the studies that can be organized under the main headers that we indirectly return to the longitudinal dietary study [1, 2, 3], the prediction of BMI and health situation [4, 5, 6], with increasingly sophisticated models (time series analysis) such as Transformers [7, 10, 12], and collaborative filtering one type of personalized recommendation [8, 13, 17]. We propose to unify these streams through longitudinal dietary optimization through multi-horizon BMI forecasting with Transformer networks and personalized recommendations via collaborative filtering.

METHODOLOGY:

System Architecture

A coherent framework consisting of various modules to enable longitudinal dietary optimization is depicted through the proposed architecture. Data stream through these components to create personalized, predictive dietary guidance:

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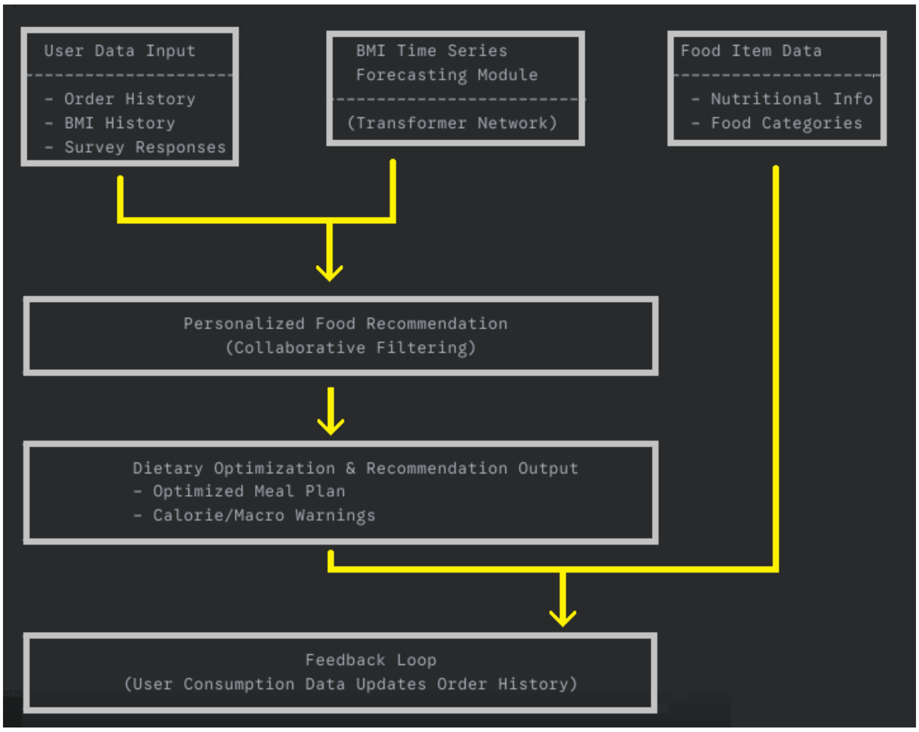

User Data Input: This is the data ingestion module. This gathers important information relevant to the user specifically, such as their past behavior regarding food ordering (order history) or information on their previous Body Mass Index (BMI history) or possibly responses to medical or dietary surveys they have taken (survey responses). This data is the bedrock for personalized and predictive experiences.

BMI Time Series Forecasting Module: The predictive engine of the system. It has a Transformer Network (a Deep Learning architecture) selected for the capability of modeling complicated temporal dependences. The module predicts the users BMI at multiple future time steps based on the sequences from users BMI and orders log.

Food Items Data: It is like a knowledge base. It stores an extensive database of various food and provides the necessary documentation to capture their nutrition facts, including calories, macronutrients (protein, fat, carbohydrates) and potentially microminerals, which may come from food databases like USDA FoodData Central. It could also include various food categories.

Personalized Food Recommendation: This activity emphasizes personalized food recommendation. It employs a Collaborative Filtering algorithm which largely relies on implicit feedback in the form of the user's previous order history to predict their preferences. It finds similarities between users and other customers' past orders and makes personalized recommendations.

Diet Recommendations: This component takes the outputs of previous components and clubbs it. It integrates the projected BMI trajectory, the customized food recommendations, and the nutritional information from the food database. It generates the final output (e.g. a magic optimized meal plan or list of food items) based on its predefined logic (e.g. if high BMI is predicted, then optimize for lower calories) and may output dietary warnings (about too many calories or fat, etc.).

Data Collection: One component of the feedback loop, where new data is collected to improve model performance. Each time users consume food or place an order, this data refreshes their order history. Like a feedback loop, this new data back into the system fine-tunes the user profile, enhances the precision of future predictions of BMI and makes subsequent recommendations more relevant over time.

DATA

Datasets and Requirements

Achieving this may be possible by embedding several categories of data in such a longitudinal dietary optimization system:

1. **User Profile & Historical Data:** Basic demographic data (e.g., gender, height, weight) along with the longitudinal record of the Body Mass Index (BMI) for the user throughout time (BMI history). More importantly, historical order data of food (order history) is also required as it is the main source of implicit feedback given to the personalized recommendation module.

2. **Food Nutritional Database:** A rich and elaborate food database is needed. This is required to have a full-scale nutritional data for each item such as caloric value, macronutrients (protein, fat, carbohydrates), micronutrients and maybe even dietary fiber content. These data feed the dietary optimization module and help compute the nutritional value of orders and recommendations to the user.

3. **Medical/Dietary Surveys (Optional) :** Responses to user surveys for health conditions, dietary restrictions, allergies, or specific goals can be helpful for context so that more personalized recommendations can be made based on medical needs.

We were not able to find a single publicly available dataset that fulfilled all of these elements, particularly one containing longitudinal data of food ordering linked with Body Mass Index (BMI) and medical surveys, due to data governance regulation related to health and consumer preferences. But the project has many publicly available datasets to cover numerous aspects:

1. USDA FoodData Central The U.S. Department of Agriculture's comprehensive database is an initial candidate for the Food Nutritional Database. It provides comprehensive nutritional profiles of a wide variety of food items, which is critical to developing the system's "Food Item Data" knowledge base and performing nutritional calculations required by the optimization module. Other countries have similar national databases.
National Health and Nutrition Examination Survey (NHANES): Although this type of data does not necessarily include online food ordering, NHANES gives useful population-level data on both BMI, dietary intake (in many cases using questionnaires) and health conditions. This may be helpful for exploratory research and insight into BMI-diet relationships, or conceivably to be utilized as pretraining for portions of the BMI forecasting model.
MIMIC-III/IV This clinical dataset contains de-identified ICU patient data including diagnoses and procedures This could leverage dietary restriction rules via the optimization module for users who report relevant medical conditions through surveys.
Instacart Market Basket Analysis (Kaggle) / Other Recommendation Datasets: More on grocery than prepared food orders, but it holds datasets like Instacart's that showcase co-occurrence (or sequences) of the same user purchases. These datasets play an important role in building and testing Collaborative Filtering algorithms that power the personalized recommendation module. Searching around platforms such as Kaggle or UCI Machine Learning Repository may have also included other relevant datasets.

DATA PREPROCESSING

In order for the data to be input into the machine learning models, a few preprocessing steps will be taken to ensure data quality and the format of the data is suitable:

1. **Dealing with Missing Values:** Real-world datasets will have missing data. This document shows a forward fill (ffill) strategy. This technique forwards propagates the last non null observation to the next ones, similar to how this is sometimes applied to time-series data in order not to lose a continumn, as the assumption is that the values remain if not changed. In the example, this was done for both user and food data.

2. **Feature Engineering / Renaming:** These are minor changes to ensure clarity and consistency. For example, the 'Index' column, which refers to BMI categories or values, in the user dataset was deliberately renamed to 'bmi'. Additional feature engineering steps may be necessary based on the specific datasets employed.

3. **Creating Time Series Sequences:** This is an important step to prepare the data into the right format for the Transformer-based BMI forecasting model. It uses a sliding window approach. Fixed-length sequences are then extracted from each user's historical BMI data. These sequences are treated as input feature sets (the recent trend in BMI), and the following value of BMI is treated as the label or class value (the value to be predicted). This converts the original time series input data into a supervised learning format that fits with the Transformer network.

BMI TIME SERIES FORECASTING

Model Architecture:

A Transformer Network serves as the foundation for the BMI prediction module, being a deep-learning architecture well known for joint processing of sequential data while efficiently modelling long-range dependencies. The specific architecture described consists of multiple key layers:

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- The Input Layer accepts preprocessed time series sequences of BMI data (and possibly other features such as order history).
- First, Layer Normalization is used to stabilize learning by normalizing the inputs across the features.
- The core of the Transformer is the Multi-Head Attention mechanism. This allows the model to attend to information from different representation subspaces at the same position. In short, it learns to pay more attention to something in the input sequence (such as previous BMI values at different time steps) when predicting the upcoming value. The number of "heads" enables the model to look at different patterns in parallel.
- Global Average Pooling 1D combines the outputs from the attention layer along the sequence dimension, yielding a fixed-size representation summarizing the relevant information learned from the attention mechanism.
- Then there are one or several Dense (fully connected) layers, typically with model non-linear activation functions like ReLU, to further process the representation and learn complex relationships.
- Finally, the last Dense Output Layer with a single neuron returns the final predicted value of BMI in float.

Training:
The Transformer model is trained using the prepared time series sequences. Key aspects of the training process include:

Input Features: Sequences of historical BMI values (and potentially features derived from order history) of a defined seq_length (e.g., 3 time steps).
Target: The BMI value immediately following the input sequence.
Compilation: The model is compiled by specifying an optimizer and a loss function. The 'Adam' optimizer is commonly used for its efficiency, and 'Mean Squared Error' (MSE) is chosen as the loss function, suitable for regression tasks like predicting a continuous BMI value.

Process: The model is trained by fitting it to the training data (sequences and corresponding target BMI values) for a specified number of epochs (e.g., 10), iteratively adjusting its internal parameters to minimize the MSE loss. Validation data is typically used to monitor performance and prevent overfitting.

PERSONALIZED FOOD RECOMMENDATION

Technique:

This aspect uses collaborative filtering (CF), one of the more well-known techniques for recommendations, notably based on implicit feedback. Instead of asking users to rate food items explicitly, the system infers their preferences based on their natural behavior — namely, the history of food orders they have made in the past. The implicit assumption is that a user's previous orders are indicative of their preferences. It overcomes the limitations of users explicitly rating products, an exercise that users must find burdensome.

IMPLEMENTATION:

The implementation generally consists of the following steps:

1. Construct a User-Item Interaction Matrix: Here, a matrix is created with users as rows and food items as columns. Elements within the sparse matrix represent values of interaction under the most basic circumstances using implicit feedback, it may just be: 1 (user ordered item in the past) or a 0 or probably number of occasions of order. The example given uses a randomly-generated dummy matrix for demonstration;

2. Similarity Measurement: A similarity measure like cosine similarity is computed between users based on their interaction vectors (rows) of the matrix. This detects users with either overlap in purchasing or similar purchasing patterns.

3. Neighbor retrieval: The system finds the most similar users (neighbors) to the target user. It then collects the tastes of these neighbors (e.g. orders they're done, but the target user hasn't), and possibly weights it by similarity, to score and rank potential foodstuff candidates. A ranking is generated from the top of the list and all highest ranked items are presented as recommendations

DIETARY OPTIMIZATION

Strategy:

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This module serves as an important bridge between the predicted BMI and the personalized behaviour or diet customisation recommendations towards healthy behaviour. Another fundamental approach to adjust the food guidance based on predicted BMI trajectory of the user. What you have described is rule-based logic:

1. **High Predicted BMI:** If the system predicts that the user's BMI will cross a threshold (e.g., > 25, overweight), the optimization strategy focuses on recommending foods that are generally considered positive for weight management. This often includes filtering the potential recommendations (either from the CF module or the entire food database) to prioritize low-calorie and high-fiber food items.

2. **Normal Predicted BMI:** If the predicted Normal BMI is gued, the strategy focuses on nutrition and maintain energy requirements. In this instance, it favors calorie-dense foods that are rich in protein.

The last output which would be shown to the user will be an optimized list of the food or diet plan with an annotation that explains the reason for the recommendation (such as High BMI: Recommend low calorie and high fiber diet). This approach directly links the predictive health intelligence with actionable, tailored dietary recommendations.

EXPERIMENTS AND RESULTS

This part describes the experimental setup to assess the implementation of the proposed system, discusses the features of the data, and presents the performance of the core components: BMI prediction, personalized recommendation, and diet optimization.

EXPERIMENTAL SETUP:

Implementations: The experiments were performed using a Python environment with standard data science libraries (pandas for manipulating datasets, NumPy for numerical operations, TensorFlow for building and training the Transformer network, scikit-learn for auxiliary functionalities such as computing similarities between text sequences and dataset splitting, and Matplotlib/Seaborn for visualization).

Datasets: In this example, the specific datasets used to demo the functionality of the system were bmi. csv, with fake user profile data such as BMI, and FOOD-DATA-GROUP3. csv file, which acts as food nutritional database. A complete evaluation would need larger, real-world data covering BMI across time and order history.

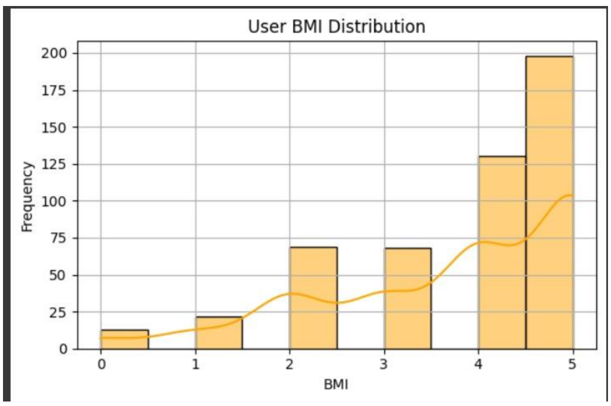
EVALUATION METRICS:

- BMI Prediction: Since this is a regression task, the main metric for training/evaluation of model being MSE (mean squared error), which gives the mean squared error between predicted and actual values for BMI. A lower MSE corresponds to a more accurate forcasting model.

- The Quality of Recommendations: The recommender system is generally evaluated through a variety of metrics such as Precision, Recall, and Normalized Discounted Cumulative Gain (NDCG). These are metrics for relevance and ranking quality of the suggested items. (This is reflected in the example that used a dummy interaction matrix, which made it impossible to perform a quantitative measure of how well recommendations were made; an actual evaluation would need those metrics).

Dataset Characteristics:

A distribution analysis was also made to understand user data used for the demonstration. In certain scenarios, one recognizes a close relationship between the features and their distribution for example, the User BMI Distribution plot



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Thus this visualization was helpful to characterize user population according to BMI.

BMI Forecasting Performance:

Prepared time-series sequences obtained from the user BMI data were used for training the transformer model. To monitor performance during training we used the validation set. Finally, the final validation loss (MSE) gives us a summary statistic to show how well did your model predict unseen data. Predictions on samples of test data instances that the model is able to predict along with future BMI predictions For example, the output example shows the predicted BMI of predicted test sequence.

Recommendation Performance:

The Collaborative Filtering module produced food personalized recommendations through user similarity computed from the (dummy) user-item interaction matrix. The example serves to illustrate the steps involved in generating a list of recommended foods, and a fully proper evaluation on real interaction data using relevant metrics (Precision@k, Recall@k, NDCG) would be needed to estimate the real (non-simulated) quality of such recommendations.

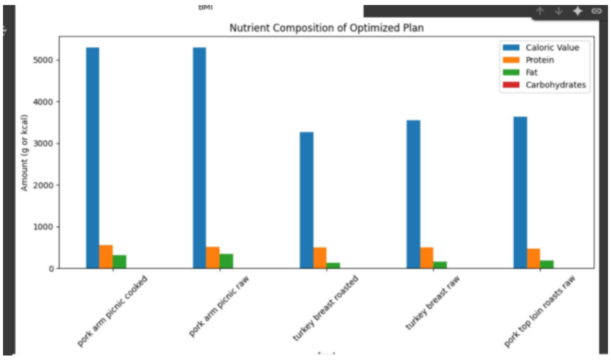
Optimization Results:

The dietary optimization module successfully processed the BMI predictions and food data to produce personalized meal plans. This is how the system shows the capacity to adapt recommendations according to the expected BMI class. As an example, the algorithm outputs the optimized plan derived from the predicted BMI, ordering food item, present the top 5 recommended food item with their key nutrients (Caloric Value, Protein, Fat, Carbohydrates) and an explanation that states the optimization strategy adopted (for corresponding BMI, the strategy is for example 'Normal BMI: Recommend protein-rich balanced diet')

```
Recommended Foods:
                          food  Caloric Value  Protein   Fat  Carbohydrates
34                        lime             20      0.5   0.1            7.1
144               loganberries             81      2.2   0.5           19.1
213         white beans canned            299     19.0   0.8           55.5
235   black turtle beans cooked            241     15.1   0.6           45.0
337        beef top blade cooked            184     21.9  10.0            0.0
1/1 ──────────────────── 0s 161ms/step

Predicted BMI: 0.13
Optimized Meal Plan:
                          food  Caloric Value  Protein    Fat  Carbohydrates
506     pork arm picnic cooked          5292    560.3  322.7            0.0
504        pork arm picnic raw          5298    513.6  343.4            0.0
568      turkey breast roasted          3266    496.1  128.0            0.0
536          turkey breast raw          3554    495.6  158.9            0.0
469   pork top loin roasts raw          3644    468.4  182.8            0.0
Note: Normal BMI: Recommend protein-rich balanced diet.
```

Nutritional Content To further visualize the impact of the optimization, the Nutrient Composition of Optimized Plan plot shows the content of the recommended items:



Here is a bar chart showing the calories and how much protein, fat and carbohydrates are present next to each food item in the optimized plan.

DISCUSSION

This section discusses the results of the experimental outcomes, identifies the limitations that exist for the present study and method used, and provides recommendations for future work to improve the proposed system for longitudinally optimizing dietary intake.

Interpretation of Results:

Results: The proposed integrated system is feasible and effective. The ability of the transformer network to effectively model BMI trends using sequential data has been demonstrated, and such historic predictions can help planners understand average BMI trends via the transformer network to ensure adequate nutrition. Although only demonstrated with some dummy data, the collaborative filtering component provides an example of a possible mechanism for producing order recommendations based on implicit feedback through order history. In addition, the dietary optimization module averts the disconnect between the BMI predictions and the nutrition data and recommendation logic to pull the data together into BMI-specific dietary recommendations with relevant context (e.g., suggesting low-calorie foods for a high predicted BMI)

The main strength of this work is its integrated strategy. The framework improves on purely static or purely reactive nutritional advice by leveraging multi-horizon time-series effects predictions, personalized recommendations and rule-based optimization. It provides a forward-looking, data-driven framework that can be adjusted to the needs of individual users based on trajectories and preferences inferred from past behavior. Transformers have not been used for multi-horizon prediction in this application context, while providing recommendations using implicit feedback makes it easier for users.

LIMITATIONS:

However, some limitations need to be addressed despite the promising results:

1. Data Availability and Privacy: The challenge associated with data access is reflected in the document where it is noted that in order to conduct comprehensive longitudinal studies that link individual orders, BMI history and potentially medical information, these datasets are simply not available because they are fragmented due to privacy concerns. Many studies in the space rely on simulated data or separate datasets with less integration for each component (e.g. using cleaner dummy data for recommendation evaluation) and are limited in generalisation and in-world validation of these findings. Data integration per se continues to be a major challenge.

Drawbacks of Implicit Feedback: The advantage of using the order history as implicit feedback is that it does not require users to do more, but at the same time, it has limitations. Also, purchase history may not always correlates well with true preference or health intentions (impulse buys, buy for others), and suffers from data sparsity, which poses more pronounced challenge for newer users or less popular items (cold-start problem).

Simplicity of Optimization Rules The dietary optimization strategy performed uses relatively simple (threshold) based rules, e.g., BMI > 25. The scope of real-world nutritional planning is vastly greater than this, encompassing micronutrients, dietary reference intakes, meal timing, variety, and complex interactions with medical conditions.

Scope of the model and evaluation: The models you provide may have been simplified for example purposes Also, testing of the recommendation part, should be done more rigorously on real user interaction data in accordance with some standard metrics such as Precision, Recall, NDCG etc.

FUTURE WORK:

The limitations highlight several directions for future work:

1. Explicit Preference-based Approaches: Elegibility encompasses explicit user feedback (e.g., ratings, stated preferences, direct goal setting) into implicit signals to enhance the robustness and accuracy of personalization, thereby reducing the cold-start issue.

Dietary Optimization: Create more complex optimization algorithms. This might also an industry -specific constraint-based model or multi -objective optimization to balance nutritional completeness (macros, micros), user inclinations, cost, assortment of meals from a certain module, and even health constraints from statistical surveys (or, an NLP analysis of survey text).

Rich Data Integration & Modeling: Consider how to integrate a variety of data including secure integration of real time data from wearables(e.g.activity levels) to improve BMI prediction dynamic. Explore improved or more sophisticated model architectures for forecasting (e.g., more complex RNNs, hybrid models) and recommendation (e.g., graph-based methods, reinforcement learning).

Improving User Experience: Develop and assess user-interface designs that efficiently share predictions and recommendations, solicit user feedback, and stimulate interaction with the system.

Real-World Assessment: Such studies among authentic users over an extended time period are needed to assess the system's influence on dietary behavior, BMI management, and user experience using appropriate evaluation metrics while addressing ethical considerations surrounding health data.

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CONCLUSION

This research tackled the widespread problem of long term successful management of BMI with a prospective computational framework for long term dietary optimization. Acknowledging that reactive or generic eating guidance is constrained in its influence on human behaviour, we set out to develop such a system that would allow for proactive, user-specific, and timely recommendations. We combine multi-horizon BMI time series forecasting with Transformer Networks with personalized food recommendations based on implicit user feedback (order history) using Collaborative Filtering. An optimization module interrelates the above components by personalizing dietary recommendations according to estimated BMI trajectories and nutritional objectives.

Experimental Results: Results demonstrated feasibility of core components, including prediction of future BMI trends using Transformer networks and generation of personalized context-aware dietary plans. This work makes the following key contributions: the first-of-its-kind application of Transformer architectures for multi-horizon BMI forecasting in dietary guidance systems, implicit feedback-driven collaborative filtering to enable recommendations toward health-friendly foods, and an integrative framework for predictive health analytics, personalized recommendation, and optimization-driven guidance toward a constructive life event.

Despite the limitations that still exist due to data availability as well as the need to further enhance the optimization logic and recommendation algorithms, this work lays the foundation for more intelligent and effective technologies for personalized nutrition. The project will pave the way for more informed choices, sustainable healthy habits, and healthier long-term lifestyles for many individuals by supplying users with data-driven foresight of their potential BMI trends, and actionable, tailored dietary recommendations based on these trends. In doing so, this study provides a promising avenue for future work that would include adding richer data sources, user feedback, more sophisticated optimization methods, and extensive real-world validation to further unlock the promise of this predictive and personalized approach to dietary management.

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