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Implementation of a personalized and healthy meal recommender system in aid to achieve user fitness goals

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***Abstract* - Recent research implies that people's urge to stay healthy and fit has drastically improved and currently, many people are in need to maintain their physical fitness incorporating healthy food habits into their lives amidst hectic urban lifestyles. Thus, nutrition applications are mushrooming in the fitness domain to aid people to improve their dietary intake, track weight-related elements, and generate meal plans. Considering the applications that are typically built for meal planning, it was apparent that personalized nutrition incorporated with healthy meal suggestions is not well addressed, and hence the need for a personalized meal recommendation system that assists the users to achieve their fitness goals is identified. Learning users' food preferences and delivering food recommendations that plead to their taste and satisfy nutritional guidelines are challenging. Due to the lack of access to a proper meal planning application or without professional help most users follow ineffective, generic meal plans which hinder them from achieving their fitness goals and often cause long-term and short-term health complications. The proposed implementation aims to bridge the gap between the existing meal planning applications and the potential need for a personalized healthy meal plan. This paper succinctly presents the design and implementation of the proposed personalized and healthy meal recommendation system and further discusses the architecture and the evaluation of the design solution.**

Keywords - automated meal planning, content-based filtering, personal nutrition, personalized meal planning, recommender system

I. INTRODUCTION

People's lifestyles have changed lately and they tend to consume more calories with less nutritional value, and these improper eating habits are extremely dangerous to one's health. It is indubitable that unhealthy eating habits can lead to deprivation of the right nutrition and eventually resulting in overweight, obesity, or malnutrition. As per the past literature, 80% of deaths referred to ten major ailments were related to improper eating habits [1]. Increased risk of strokes, diabetes, cardiac diseases, cancers, tooth decay, osteoporosis, depression symptoms, high cholesterol levels, high blood pressure are some remarkable short-term and lifelong ailments that could implicitly exhibit in individuals due to poor nutrition [2]. Global nutrition statistics demonstrated that people do not have adequate knowledge about the right nutrition which later results in macronutrient malnutrition [3]. Moreover, healthy meal planning requires a discerning knowledge about nutritional adequacy, gender, age, and level of physical activity which in most cases act as an obstacle to most individuals. Hence, even though healthy meal planning is starting to gain attention among people, these barriers discourage individuals from adjusting their food habits to favor a healthier diet. The unavailability of finding healthy food alternatives that fit user tastes acts as one of the main barriers among individuals which hinders them from achieving their fitness goals. Learning users' meal preferences is a mandatory step in recommending healthy foods that users are more likely to find desirable. Despite the presence of personalized meal planning applications which have been specifically designed for the personalization of meal plans, many approaches still suffer from major limitations. PlateJoy [4], a personalized meal planning application, elicits users' meal preferences in the form of a questionnaire.

"(a) How often do you eat meat? No restrictions, No Red Meat, Pescatarian, Flexitarian, Vegetarian, Vegan

(b) Are there ingredients you prefer to avoid? Added sugar, Avocado, Beef, Bell pepper, Chicken"

Depending on the users' answers to the questions the application recommends a meal plan by avoiding distinctly unacceptable food choices made by the user, and thus only capable of recommending a meal plan of coarse-grained food preferences. Moreover, the application only focuses on delivering a personalized meal plan without embedding the nutritional guidelines.

Another main barrier that has been identified by the authors is the lack of meal planning approaches that take user's physiological data and plan their meals to meet the daily nutritional requirements by incorporating standard nutritional guidelines.

It is proven that the adoption of the right nutrition practices has been shown to be beneficial to prevent many non-communicable diseases [1] [5]. Drawbacks and limitations of previous meal planning approaches call the sheer lack of a meal planning system that correctly caters to meet the user's nutritional requirements and user's meal preferences. Hence, the proposed solution presents a meal planning approach that is focused on mitigating the issues in the meal planning domain and delivering the following features.

1. The delivery of a meal planning approach that delivers fine-grained user preferences by learning the user's meal preferences.

2. The delivery of a meal planning approach that integrates the nutritional guidelines to cater nutritional requirements of the user.

Personalization of meal planning is a lively research hitch focused on adding personalization capabilities in the meal recommendation domain. Recommender systems have been identified as the most successful tool which is capable of personalizing processes over several domains [6]. E-commerce [7], finance, marketing, tourism [8], and many other domains are using recommender systems to support users to deliver recommendations in an overloaded information context [9]–[13]. The proposed implementation contributes at developing and integrating a recommender system model that incorporates both user preferences and nutritional requirements in the food recommendation domain.

The proposed system will get users basic information (age, weight, height, gender) and user goals (weight loss/ weight gain/ maintain current weight) followed up by user meal preferences by asking a simple questionnaire. The level of physical activity (sedentary, lightly active, moderately active, very active) is taken as an input to the meal recommendation system as a parameter of the physical level of engagement of the user. The system then queries the Basal Metabolic Rate (BMR) and estimates the Daily Calorie Allowance for the user depending on the fitness goal based on various nutrition health measurements [14] [15]. The proposed system finally presents a weekly meal plan to achieve the user's fitness goal that fulfills the nutritional requirements of the user after refining the meals to best match with the user's taste. This paper is focused on developing a personalized meal recommendation system for healthy users that will eventually prevent the users from major chronic diseases related to unhealthy eating habits.

The remainder of the paper is organized as follows. Section II discusses the existing approaches in the meal planning domain and their corresponding gaps. Section III presents the design approach of the proposed implementation and section IV further discusses the system design architecture of the overall solution. Section V discusses the implementation of the proposed personalized and healthy meal planning system. Section VI presents the evaluation of the proposed system and section VII comprises the discussion. Section VIII finally concludes the paper.

II. Related Work

Referring to the preceding literature, it is recognized that a multitude of studies have been conducted in the meal planning domain over the past years [16]–[23]. This section discusses the related work conducted on the food recommendation domain with correspondence to their gaps.

Eat This Much approach provides users with daily pre-defined meal plans fulfilling Calorie Intake (CI) level as stated by the user as a user input [24]. However, this approach has some limitations. This allows the user to select his meal preferences by distinctly avoiding certain food categories rather than allowing them to log their food preferences directly into the system which will finally result in suggesting coarse-grained food preferences. The approach does not deliver a meal plan adhering to the nutritional guidelines; hence the approach does not address the requirements of the user group who lacks adequate nutritional knowledge and thus fails in delivering a healthy meal recommendation.

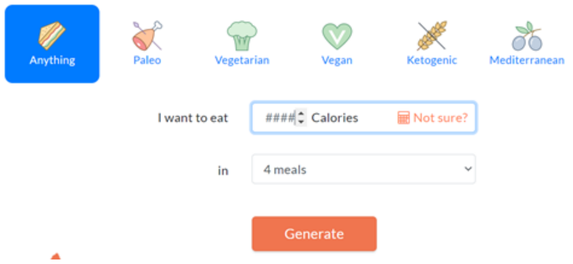


Fig.1. Screenshot of Eat-this-much application

MakeMyPlate approach lets the user restore an already existing recipe with another [25]. But the drawback of this approach is that the system doesn't substantiate as to whether the replaced recipe is calorically equivalent with the initial recipe substituted by the user. Therefore, substituting meals as per the desire of the user might result in a caloric imbalance between the original meal and the replacement meal. Additionally, the approach does not deliver personalized meal recommendations to match the user's taste.

Another existing meal planning approach is MyFitnessPal which takes in the user's physiological information, desired weight, and outputs the daily calorie allowance for the user [26]. The approach does not display any intelligent behavior. It merely acts as a calorie counter for a particular user without even setting up meal plans.

The authors in [27] present the use of ingredient substitution on how ingredients can be fit well together as a means to get personalized recommendations. By observing the observations and the test results, authors in [27] have concluded that this approach can predict users' preference for a recipe, but the whole list of ingredients is not taken into consideration. This research only focuses on predicting food recipes that adhere to user preferences and doesn't take the fitness goal of the user into consideration.

Table I summarizes the existing approaches in the meal planning domain in relation to the tracking of calorie consumption, delivery of personalized meal recommendations, and adherence to the nutritional guidelines.

TABLE I. Summary of Existing Approaches in Meal Recommendation Domain

Related work	Tracking of calories allowed	Delivery of personalized meal plans	Adherence to nutritional guidelines
Eat-This-Much [24]	✔		
Make My Plate [25]	✔		
MyFitnessPal [26]	✔		
LoseIt [28]	✔		
PlateJoy [4]	✔	✔	
Teng et al. [27]	✔		
Yang et al. [29]	✔	✔	✔
Nutrino [30]	✔	✔	
BNF's Meal Plan [31]			✔

Following the existing approaches in the meal recommendation domain, it is identified that the taken approaches are not focused on delivering a healthy meal plan which is fine-grained to the user's personal preferences.

The authors in [29] presented an approach to deliver a personalized and a healthy meal plan. However, their approach was limited to research on exploiting visual food features. Hence the approach followed in this paper will adhere to the delivery of a personalized and a healthy weekly meal plan to achieve the fitness goals of the users.

III. Design Approach

This section describes the design approach of the proposed system with detailed explanations with relevance to the selection of the most appropriate technology in the context of use. The proposed implementation of the personalized and healthy meal recommender system is designed in a way by considering the user group opinions gathered from the initial survey conducted by the authors and by addressing the gaps of existing meal planning approaches in the domain and by incorporating nutritional measurements as depicted in Fig. 2.

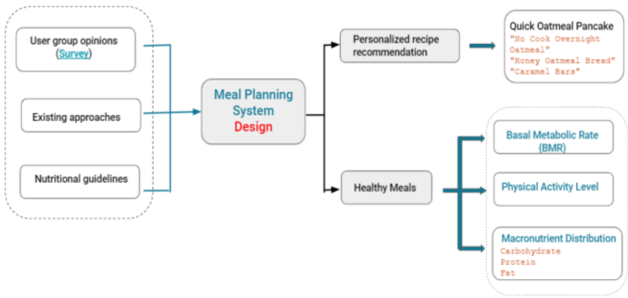


Fig.2. System design of proposed implementation

A. *Initial survey*

It was decided to conduct an initial survey to capture the sentiments of the individuals and to verify the perception held by individuals regarding the meal planning approaches. Additionally, the survey was aimed at understanding the barriers related to personalized and healthy meal planning. The survey was conducted targeting Sri Lankan individuals both residents and overseas Sri Lankans. The sample size of the survey was 103 participants. The participants were assessed based on their nutritional knowledge on meal preparation and asked to state their opinions on the need for a personalized and healthy meal plan to use in aid to achieve their fitness goals. A summary of the responses gathered is depicted in Fig. 3 and Fig. 4.

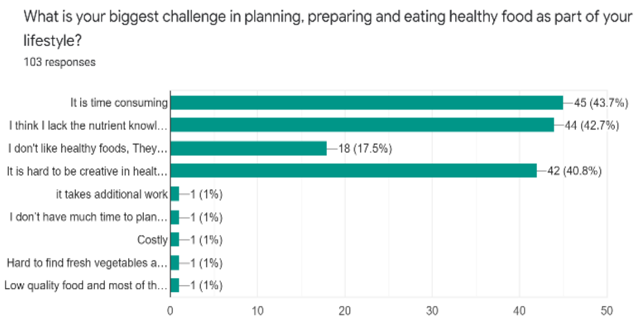


Fig.3 Challenges faced by individuals in healthy meal planning.

Fig. 4. Summary of responses for the need of the system.

The initial survey was additionally aimed at gathering the fitness goals of the general public, energy intake, physical activity level of individuals, other hindrances in healthy meal planning in order to deliver a more user-friendly meal planning approach. According to the nutritional survey statistics that have been conducted previously and as per the results obtained from the initial survey, only less than 5% of the participants could answer the knowledge about macronutrients (carbohydrate, protein, and fat) correctly. Moreover, 83 participants out of 103 participants, a percentage of 80.6% have stated the need for a personalized and healthy meal recommender system as in Fig.4 and hence the requirement for the proposed implementation was verified.

B. *Selection of recommender system*

The design for the recommender system in the proposed implementation has been conceived in an attempt to overcome the limitations faced by existing meal recommendation approaches. Hence, the most suited recommender system needs to be integrated into the system to deliver more fine-grained meal preferences by learning the taste of the user.

Gunawardana and Shani [32] identify two main tasks related to recommender systems as prediction task and recommendation task. In relation to the context of use and the working principles beneath the Recommendation Systems, RSs have been classified into some popular groups namely collaborative filtering, content-based filtering, and demographic filtering. Other categories are knowledge-based and constraint-based recommender systems [33]. Out of the aforementioned popular categories of RSs, content-based and collaborative filtering recommender systems are successful in the personalization process.

Authors in [34] have used collaborative filtering methods in the recommendation of food recipes and have concluded that content-based filtering strategies can be used to achieve more sensible accuracy and coverage. They have found only a marginal boost in the accuracy when collaborative filtering strategies are utilized [34]. Another major problem of the collaborative filtering approach is the method of combining and weighing the preferences of user neighbors. Knowledge-based recommender systems use users' preferences in the recommendation and the constraint-based recommender approach sets constraints like daily fat, carbohydrate, and protein intake limitations.

Content-based recommender systems rely on meta-data or features from individual items to recommend items that can be used in this context. Content-based filtering has been constructed to recommend similar item recommendations by analyzing the content of the user's previous preferences [33]. Hence, the approach followed in this paper will adhere to the content-based filtering methodology with consideration to the context of use.

As authors in [35] addressed, embedding more rules and constraints in the recommender system will help in the improvement of the accuracy of the recommender system. The right balance between the nutritional needs of the user and the user's taste needs to be acknowledged rather than delivering recommendations in an isolated fashion. For instance, recommendations only based on user preferences may invigorate unhealthy eating patterns. Thus, the originality of this work also lies in coalescing more nutritional constraints in the system concerning user's physiological information and delivering fine-grained user-preferred meal plans.

IV. System Design Architecture

The design architecture of the overall system is presented in this section with detailed designs and explanations, prioritized by the sequence of the design. To address the issue at hand, the authors have proposed a meal recommendation module consisting of a query module, recommender system, and a knowledge base (recipe data and nutritional information) as illustrated in Fig. 5.

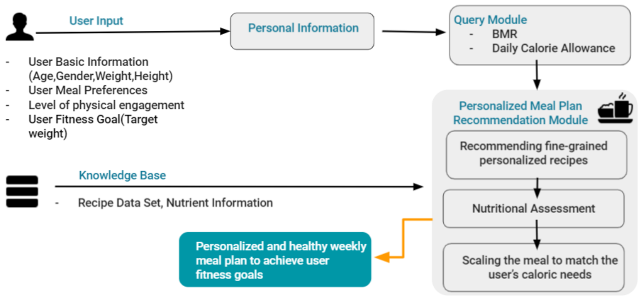


Fig.5. System design of the proposed implementation

The proposed implementation delivers an encompassment of a multitude of competence suited for recommending a personalized and healthy meal plan to achieve user fitness goals. The user's physiological information such as age, gender, current weight, height is taken as inputs to the system. Additionally, the goal weight of the user is taken as the fitness goal of the user. The user's fitness goal might be to lose weight, gain weight, or maintain the current weight. Therefore, meal recommendation is done in the order of the following steps.

1. Calculation of the user's caloric needs in correspondence to his BMR and the goal weight.
2. Delivery of fine-grained personalized meals to plead the user's taste.
3. Translation of daily calorie allowance into an actual meal plan and, optimizing and scaling the personalized meal recipes to meet the daily caloric allowance and the daily macronutrient requirement of the user.

The query module is specifically designed to compute the Basal Metabolic Rate (BMR) to determine the Daily Calorie Allowance of the user based on user inputs of age, gender, weight, height, and fitness goal. Harris-Benedict [36] equations and Mifflin St. Jeor [37] equations are the most adopted formulas used by nutritionists in the calculations of Basal Metabolic Rate. The Mifflin St. Jeor equation is able to assess the weight more accurately with the changes in the lifestyle. In comparison to the Harris-Benedict formula, Mifflin St. Jeor's formula is having an improvement of 5% in the accuracy [38]. The following equations (Eq.1 and Eq.2) account for determining the BMR of males and females using the Mifflin St. Jeor formula.

(1) $$BMR_{male} = 10 * weight + 6.25 * height - 5 * age + 5 \quad (1)$$

(2) $$BMR_{female} = 10 * weight + 6.25 * height - 5 * age - 161 \quad (2)$$

To query the Total Energy Expenditure, BMR and the level of physical activity (PAL value) is taken into consideration. Energy expenditure and energy requirement are highly dependent on the Physical Activity Level (PAL). The level of physical activity is classified into 5 main categories by the 1981 FAO/WHO/UNU expert consultation (WHO, 1985) and given a range of PAL values based on the level of physical activity as stated in Table II [39]. Thus, Total Energy Expenditure can be calculated by multiplying the BMR and the corresponding PAL value given concerning the level of physical activity of the user.

Table II. Classification of Lifestyle as per the Level of Physical Activity

Category	PAL value
Sedentary (little or no exercise)	1.2
Lightly active(light exercise/sports 1-3 days/week)	1.375
Moderately active (moderate exercise/sports 3-5 days/week)	1.55
Very active (hard exercise/ sports 6-7 days a week)	1.725
Extremely active, hard daily exercise or physical job	1.9

Body mass change is associated with the daily caloric deficiency or a caloric surplus. A calorie deficiency results in weight loss while a calorie surplus results in weight gain. Likewise, a caloric balance between the caloric intake and the caloric expenditure results in maintaining the weight. As per the research conducted by the National Institute of Health in the USA, 3500 kcals per pound (0.45kg) rule can be used in achieving the fitness goals in the nutrition domain which states that cumulative energy deficiency of 3500 kcals is the equivalent of the loss of 1 pound per body weight [40]. The weekly steady rate of weight loss is considered to be one pound (0.45kg) i.e., 500 Kcal daily deficiency. Accordingly, a daily caloric surplus of 500kCals would result in a weight gain of 1 pound per week. Health Promotion guidelines state that Caloric Intake estimations for adult females and males range from 1600 to 2400 and 2000 to 3000 respectively based on their level of engagement of physical activity [41]. Moreover, females and males are not recommended to consume less than 1200 and 1500 kcals respectively [41]. Therefore, when recommending the daily calorie allowance to achieve user fitness goals, the aforementioned rules have been implemented in the proposed implementation of the personalized and healthy meal recommender system. The proposed implementation is designed in a way to suggest the number of weeks (n) to reach the expected target weight (w') of the user (Eq. 3).

$$n = \frac{1}{7}\left(\frac{|w-w'|}{\frac{|CI-TEE|}{500}}\right) \quad (3)$$

After querying the daily calorie allowance (CI), the personalized meal plan recommendation module aims at giving out personalized and healthy meal recommendations by translating the calculated caloric intake into an actual meal plan as sketched in Fig.5. This module uses a content-based recommender system to deliver fine-grained personal preferences. The content-based model fabricated in this research utilizes Latent Dirichlet Allocation (LDA) as a topic model to generate tags to group similar items of the recipes in the dataset in order to finally recommend personalized recipes based on the user's previous meal preferences. The similarity between the user preferred meal and all the recipe profiles in the dataset is obtained from cosine similarity. This is a semantic similarity measure that takes the cosine angle of two vectors to calculate the similarity as stated in Eq.4 [33].

$$sim(i,j) = \frac{r_i \cdot r_j}{\|r_i\|_2 \|r_j\|_2} = \frac{\sum_u \; r_{i,u} r_{j,u}}{\sqrt{\sum_u \; r_{i,u}^2}\sqrt{\sum_u \; r_{j,u}^2}} \quad (4)$$

In the proposed implementation, the user is given the chance to enter at least 3 user-preferred recipes via the application. During recommendation, the cosine similarity metrics are calculated from the recipes' feature vector and the user's preferred feature vector retrieved from user input. Hence the top 100 recipes are recommended in the descending order of similarity score to best match the recipes w.r.t user-preferred meals.

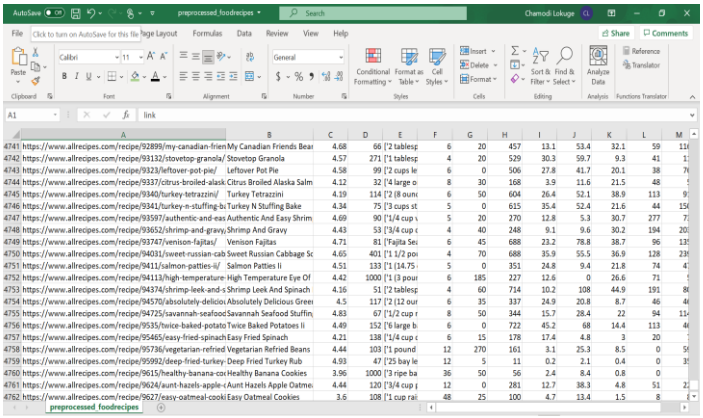
Subsequently, this initial set of personalized recipes is passed into the Nutritional Assessment Module. This module is designed to translate the daily caloric allowance into an actual meal plan by taking macronutrient distribution into consideration. The system will utilize the recommended daily protein requirement (>= 0.8g/kg/day) as per the standard dietary guidelines and hence satisfy the daily protein need of the user [42]. Moreover, the system filters the fat percentage of the recommended recipes to be a minimum of 40% as recommended in guidelines in order to deliver a healthy meal recommendation [43]. After determining the appropriate macronutrient composition, the final phase of the personalized meal planning is to optimize the top-recommended recipes by the content-based recommender system. To do so, the top recipes recommended by the content-based recommender system are scaled to match the user's caloric need and filtered based on the rules implemented by the nutritional assessment module. The daily calorie allowance of the user is distributed equally among breakfast, lunch, and dinner. The proposed implementation finally outputs a weekly meal plan for breakfast, lunch, and dinner with the number of calories, portion size, link for the recipe, and a pie chart for macronutrient composition of the recommended recipe.

V. System Implementation

This section describes the implementations carried out in each component of the system with regards to the methodologies and designs described in the previous sections.

A. *Data set preparation*

The recipe data set is scraped from allrecipes.com using python, selenium, and chrome web driver. Over 5000 recipes are scraped including the title of the recipe, ingredients, ratings, cook time, servings, calorie, protein, carbohydrate, cholesterol, fat, sodium, and ranking of the recipe. The recipe data with no nutritional information is eliminated and data types for cook time, calorie, protein, carbohydrate, fat, and rankings are changed to int and float data types. NLTK and Gensim libraries are used to clean and preprocess the dataset. Fig.6. illustrates a screenshot of the preprocessed dataset.



	A	B	C	D	E	F	G	H	I	J	K	L	M
4741	https://www.allrecipes.com/recipe/92899/my-canadian-frien	My Canadian Friends Bear	4.68	66	['2 tablesp	6	20	457	13.1	53.4	32.1	59	11
4742	https://www.allrecipes.com/recipe/93132/stovetop-granola/	Stovetop Granola	4.57	271	['1 tablesp	4	20	529	30.3	59.7	9.3	41	1
4743	https://www.allrecipes.com/recipe/9323/leftover-pot-pie/	Leftover Pot Pie	4.58	99	['2 cups le	6	0	506	27.8	41.7	20.1	38	7
4744	https://www.allrecipes.com/recipe/9337/citrus-broiled-alask	Citrus Broiled Alaska Salm	4.12	32	['4 large o	8	30	168	3.9	11.6	21.5	48	
4745	https://www.allrecipes.com/recipe/9340/turkey-tetrazzini/	Turkey Tetrazzini	4.19	114	['2 (8 ounc	6	50	604	26.4	52.1	38.9	113	9
4746	https://www.allrecipes.com/recipe/9341/turkey-n-stuffing-ba	Turkey N Stuffing Bake	4.34	75	['3 cups st	5	0	615	35.4	52.4	21.6	44	15
4747	https://www.allrecipes.com/recipe/93597/authentic-and-eas	Authentic And Easy Shrim	4.69	90	['1/4 cup v	5	20	270	12.8	5.3	30.7	277	7
4748	https://www.allrecipes.com/recipe/93652/shrimp-and-gravy/	Shrimp And Gravy	4.43	53	['3/4 cup c	4	40	248	9.1	9.6	30.2	194	20
4749	https://www.allrecipes.com/recipe/93747/venison-fajitas/	Venison Fajitas	4.71	81	['Fajita Sea	6	45	688	23.2	78.8	38.7	96	13
4750	https://www.allrecipes.com/recipe/94031/sweet-russian-cab	Sweet Russian Cabbage Sc	4.65	401	['1 1/2 pou	4	70	688	35.9	55.5	36.9	128	23
4751	https://www.allrecipes.com/recipe/9411/salmon-patties-ii/	Salmon Patties Ii	4.51	133	['1 (14.75	5	0	351	24.8	9.4	21.8	74	4
4752	https://www.allrecipes.com/recipe/94113/high-temperature-	High Temperature Eye Of	4.42	1000	['1 (3 pour	6	185	227	12.6	0	26.6	71	
4753	https://www.allrecipes.com/recipe/94374/shrimp-leek-and-s	Shrimp Leek And Spinach	4.16	51	['2 tablesp	4	60	714	10.2	108	44.9	191	8
4754	https://www.allrecipes.com/recipe/94570/absolutely-deliciou	Absolutely Delicious Green	4.5	117	['2 (12 our	6	35	337	24.9	20.8	8.7	46	4
4755	https://www.allrecipes.com/recipe/94725/savannah-seafood	Savannah Seafood Stuffing	4.83	67	['1/2 cup r	8	50	344	15.7	28.4	22	94	11
4756	https://www.allrecipes.com/recipe/9535/twice-baked-potato	Twice Baked Potatoes Ii	4.49	152	['6 large b	6	0	722	45.2	68	14.4	113	4
4757	https://www.allrecipes.com/recipe/95465/easy-fried-spinach	Easy Fried Spinach	4.21	138	['1/4 cup c	6	15	178	17.4	4.8	3	20	
4758	https://www.allrecipes.com/recipe/95736/vegetarian-refried	Vegetarian Refried Beans	4.44	103	['1 pound	12	270	161	3.1	25.3	8.5	0	5
4759	https://www.allrecipes.com/recipe/95992/deep-fried-turkey-	Deep Fried Turkey Rub	4.93	47	['25 bay le	12	5	11	0.2	2.1	0.4	0	3
4760	https://www.allrecipes.com/recipe/9615/healthy-banana-coo	Healthy Banana Cookies	3.96	1000	['3 ripe ba	36	50	56	2.4	8.4	0.8	0	
4761	https://www.allrecipes.com/recipe/9624/aunt-hazels-apple-c	Aunt Hazels Apple Oatmea	4.44	120	['3/4 cup p	12	0	281	12.7	38.3	4.8	51	2
4762	https://www.allrecipes.com/recipe/9627/easy-oatmeal-cooki	Easy Oatmeal Cookies	3.6	108	['1 cup rai	48	25	100	4.7	13.4	1.5	8	

Fig.6. Screenshot of the preprocessed dataset

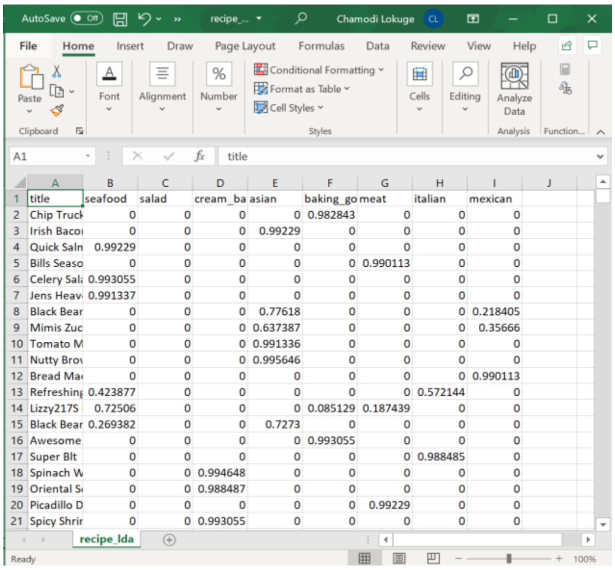
B. *Content-based recommender system*

In order to recommend fine-grained personalized recipes, it is important to provide labels to each recipe in the preprocessed dataset. For this topic-modeling purpose, authors have utilized the LDA model to have probability distribution across labeled topics as discussed in section IV. The LDA model is implemented after choosing the optimal number of topics and, by tuning the hyperparameters to improve the accuracy of the model as further discussed in section VI under evaluation of the recommender system. Fig.7 depicts the parameters used to build the optimized LDA model.

```
lda_model_final = LdaMulticore(corpus=corpus,
                               id2word=id2word,
                               num_topics=8,
                               random_state=100,
                               chunksize=100,
                               passes=10,
                               alpha=0.01,
                               eta=1)
```

Fig.7. Building the LDA model

Next, the LDA model is used to create an LDA matrix that holds the probability distribution for every recipe in the dataset as presented in Fig.8. Probability distribution retrieved from the LDA matrix is utilized in the content-based recommender system to deliver personalized recipes based on the user's preferred recipes.



	title	seafood	salad	cream_ba	asian	baking_go	meat	italian	mexican
2	Chip Truck	0	0	0	0	0.982843	0	0	0
3	Irish Bacon	0	0	0	0.99229	0	0	0	0
4	Quick Saln	0.99229	0	0	0	0	0	0	0
5	Bills Seaso	0	0	0	0	0	0.990113	0	0
6	Celery Sal	0.993055	0	0	0	0	0	0	0
7	Jens Heav	0.991337	0	0	0	0	0	0	0
8	Black Bear	0	0	0	0.77618	0	0	0	0.218405
9	Mimis Zuc	0	0	0	0.637387	0	0	0	0.35666
10	Tomato M	0	0	0	0.991336	0	0	0	0
11	Nutty Brov	0	0	0	0.995646	0	0	0	0
12	Bread Ma	0	0	0	0	0	0	0	0.990113
13	Refreshing	0.423877	0	0	0	0	0	0.572144	0
14	Lizzy217S	0.72506	0	0	0	0.085129	0.187439	0	0
15	Black Bear	0.269382	0	0	0.7273	0	0	0	0
16	Awesome	0	0	0	0	0.993055	0	0	0
17	Super Blt	0	0	0	0	0	0	0.988485	0
18	Spinach W	0	0	0.994648	0	0	0	0	0
19	Oriental S	0	0	0.988487	0	0	0	0	0
20	Picadillo D	0	0	0	0	0	0.99229	0	0
21	Spicy Shrir	0	0	0.993055	0	0	0	0	0

Fig.8. Screenshot of the probability distribution of topics in the dataset

C. *Web application*

The proposed system is implemented as a web application using python for the server-side development and the application is deployed in streamlit. The application takes in the user's personal information (age, gender, current weight, and height), user target weight, and user meal preferences via the user interface of the application. Fig.9 and Fig.10 demonstrate the UI implementation of the web application.

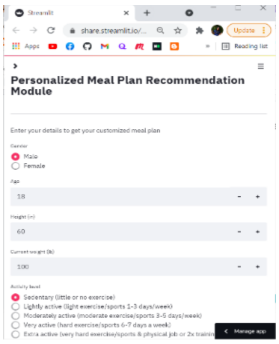


Fig.9. UI implementation of web application

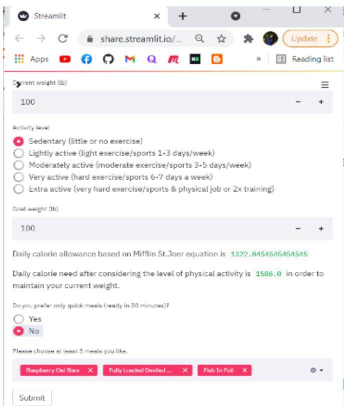


Fig.10. UI implementation of web application

The proposed implementation allows the user to add an optional filter for cook time to recommend recipes to prepare meals in less than 30 minutes. This was a user suggestion in the initial survey conducted by the authors at the initial phase of gathering user requirements. Upon the submission of the required information, the application outputs a weekly meal plan for breakfast, lunch, and dinner as demonstrated in Fig.11.

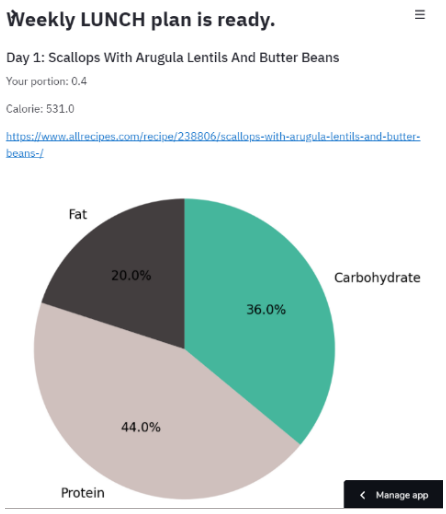


Fig.11. UI implementation of web application

VI. EVALUATION

The following section describes in detail how the proposed implementation of the personalized meal recommendation module is evaluated using different approaches, namely: (A) the validation and correctness of the recommender system, (B) evaluation by a real audience to determine the success at meeting the initially set objectives of the project.

A. *Evaluation and validation of the recommender system*

In order to test the quality of a recommendation system model, several evaluation metrics can be employed. The recommender system model incorporated in the proposed implementation is the Latent Dirichlet Allocation (LDA) model. This section describes a quantitative evaluation of the LDA model. Topic coherence and perplexity measures are some adopted intrinsic evaluation metrics that can be used to judge how good a given model is [44]. There were studies that argue the perplexity measure is sometimes not correlated with the human judgment of the model [45]. Thus, topic coherence is used to measure the semantic similarity between topics inferred by the model.

The LDA model is initially developed with 10 different topics where each topic is a mix of keywords and each keyword contributes a certain weightage to the topic. The baseline coherence score is 0.383 when the LDA model is built with default settings. The optimum number of topics needs to be determined in order to improve the baseline coherence score of the model. The graph in Fig. 12 presents the coherence score (c_v) over the number of topics (n). The highest coherence score is yielded when the number of topics is in the range of 7 to 8.

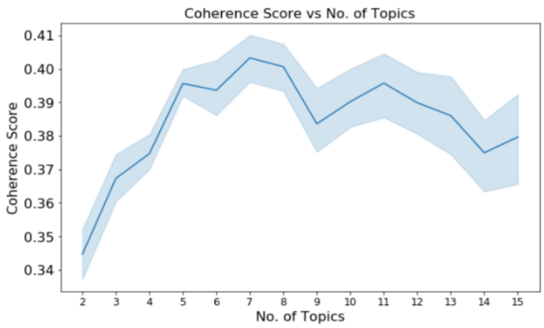


Fig.12. Coherence score over # of topics to determine the optimal # of topics

Additionally, optimal document-topic density (alpha) and word-topic density (beta) parameters need to be determined to improve the coherence score of the model. Using the LDA tuning results, it was observed that using a topic distribution of 8 and alpha of 0.01 and beta of 1, an improvement of 9.138% in coherence score over the baseline coherence value can be achieved.

Mean cosine similarity between content-based recommender system and raking-based recommender system for 1000 simulations is considered in order to validate the content-based recommender system. Ranking based recommender system is implemented to suggest recipes based on the ‘ranking’ of the recipes. Content-based recommender system is implemented to randomly pick 3 recipes to mimic the user behavior of choosing meal preferences via the web application. Both the systems were filtered based on the rules developed in the nutritional assessment module. Based on the results, the content-based recommender system scores a mean cosine similarity of 0.47 and the rank-based recommender system scores a mean similarity of 0.23 where the content-based recommender system scores remarkably a high mean similarity for 1000 simulations. The graph in Fig.13 illustrates the comparison between the mean similarity score of the two systems over 1000 simulations.

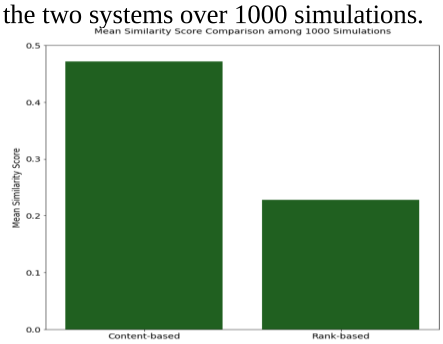


Fig.13. Graph of mean similarity score of content-based and rank-based systems

A. *Evaluation by a real audience using the post-evaluation survey*

Considering the initially set objectives in developing a personalized and healthy meal planning approach, it was decided to evaluate the system using a post-evaluation survey upon the completion of the relevant implementations. For evaluating the effectiveness of the proposed implementation, it was planned to conduct the experiment by allowing the participants to use the application deployed in streamlit over a period of one week. Phase 1 of the post-evaluation survey aimed at targeting 10 individuals from Sri Lanka. Participants were given an introduction about how to use the application and asked to assess the application based on their user experience after the completion of the week. Following the completion of one week, all the responses of the 10 individuals were collected.

The majority of the participants rated the application positively as shown in Fig. 14. The country was in a locked-down state when the experiment was conducted thus people were not allowed to step out to prepare the meal plans suggested by the system. Hence, none of the participants have used the meal plans recommended by the system. Moreover, the recipe data set used is scraped from allrecipes.com which includes foreign recipes which was a drawback in the participants’ point of view.

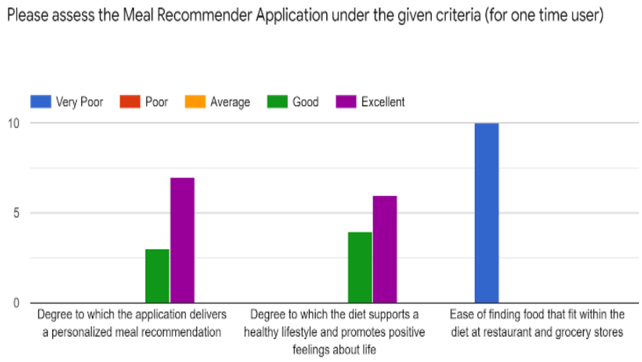


Fig.14. Summary of post-evaluation survey phase 01(one-time user)

Meals suggested by the application are mostly Malaysian, Japanese, and Australian cuisines. Therefore, it was decided to conduct Phase 02 of the post-evaluation survey targeting Sri Lankan participants currently living in Japan, Australia, and Malaysia.

As all of the participants are supposed to follow healthy meal plans, it was decided to choose individuals from a social media fitness group who are keen on planning their meals healthy. Among the individuals selected, 5 participants have followed the diet plan recommended by the application over a week. The majority of the participants rated the experience of the application from average to excellent. All of the participants have confirmed that the meals suggested by the application are personalized, healthy, and support the individuals in achieving their fitness goals. Fig.15 depicts the summary of ratings of post-evaluation survey phase 02 based on a one-week user experience.

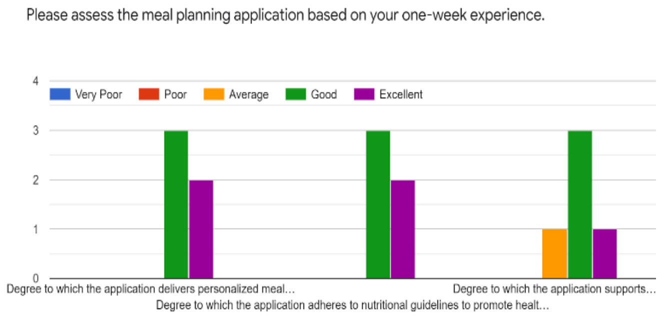


Fig.15. Summary of post-evaluation survey phase 02(one-week user experience)

VII. Discussion

The existing studies in the meal planning domain focus solely on the meal plan generation task, while this paper proposes to provide a full-fledged solution for a more personalized and nutritional meal plan to achieve the fitness goals of the user. In general most of the food recommender systems play a better role in tracking the calorie consumption of the user, but do not adhere to provide the user the adequate nutritional needs or to help the user to achieve fitness goals [16], [17], [19]–[29], [34], [42], [46]–[59]. The primary objective of this paper is to understand the obstacles related to meal planning and thus, mitigate the shortcomings of delivery of a personalized and healthy meal plan.

The initial survey responses concluded that the majority of the individuals out of the 103 participants did not have adequate knowledge to plan their meals healthily. 80.6% of the participants were aware that unhealthy eating habits lead to major health diseases and over 80% of participants would likely to use a meal planner. It was evident that participants lack the adequate nutritional knowledge to plan their meals from the responses of the nutritional survey conducted along with the initial survey. It was mostly cumbersome to stick to a meal plan which did not go hand in hand with user taste. Based on the responses, participants have claimed the necessity of a meal of their choices which follows nutritional guidelines as presented below [60].

"I think many people lack the nutritional knowledge and do not know how to loose weight or gain weight by keeping track of their meals."

"I do not tend to learn or keep track of all the nutritional values of the food I consume, so it's best to let a meal planner take care of it to me. But this again depend on how intrusive such an option in day to day life would be, for example having to consume food that do not align with my tastes is a negative."

"I would always prefer to stick to a healthy and personalized meal plan. But since I lack the nutritional knowledge on how to prepare a meal plan on my own, I would surely use a meal planner that does the work for me."

By analyzing the results obtained from the initial survey, it was determined that there exists a need for personalized and healthy meal plans in aid to achieve user fitness goals [60]. It was also identified that a combination of personalized and healthy meal planning approaches is favorable for many users.

Presenting a new web application and leaving a positive impression while engaging in the application is challenging. The authors of the proposed system ensure that the user interface (UI) design encompasses minimalistic UIs to make the application visually appealing to deliver a more aesthetically pleasing experience to motivate the users to follow along. The user requirements and perceptions about existing meal planning approaches are gathered during the initial phase of planning the system and thus the system is designed in a way to eliminate the complicated UIs and over flooding of information. The macronutrient distribution of the recommended recipes suggested by the system illustrates in pie charts to make more sense to the user that later got positive comments in the post-evaluation survey.

The authors have conducted three surveys from the initial stage of planning the design, to the final phase of the proposed implementation. The results of the surveys are summarized below.

1. Out of 103 individuals who participated in the initial survey, a majority of them know that unhealthy eating habits lead to major ailments and hence in need of a personalized and healthy meal recommendation application.

2. The participants of the post-evaluation survey have concluded that the proposed implementation of the personalized meal planner application delivers healthy meal plans and supports in achieving their fitness goals.

3. Overall a positive perception was observed in the participants regarding the helpfulness of the implemented meal recommendation application for the users to achieve their fitness goals.

A. Limitations

One of the major limitations of the design methodology of the proposed implementation is currently the application is targeting healthy individuals with no medical complications. Due to the complexity of dealing with medical cases, and since it needs a lot of expert intervention, the current implementation of the proposed system aimed at delivering a healthy meal plan to a healthy user which will ensure that a user follows a healthy diet. It was evident that people eating unhealthy food choices and lacking the knowledge of nutrition may eventually lead to major chronic diseases which ultimately lead to premature death. Hence, the proposed implementation aims to deliver healthy meal recommendations which also pleads with their taste.

VIII. Conclusion and Further Work

Following the inspection of existing meal planning approaches and their gaps, this paper presents a meal planning approach both personalized and healthy in aid to achieve user fitness goals. According to the past literature and the observations gathered during the various stages of design methodology, the following conclusions regarding the involvement of personalization and nutritional guidelines in the food recommendation can be identified.

1. Delivery of a meal recommendation application considering the user's meal preferences motivates the user to follow a healthy meal plan.
2. Delivery of a meal recommendation application considering nutritional constraints like macronutrient distribution has a positive impact in achieving the user fitness goals.
3. Delivery of a combination of both personalized and healthy meal recommendations is optimal for greater impact in achieving user fitness goals.

Further work of this paper will include an investigation of the possibility to integrate the capability of considering medical complications of the users in the meal recommendation.

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