PIN prototype for Intelligent Nutrition Assessment and Meal Planning

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***Abstract*—This paper briefly describes and evaluates Personal Intelligent Nutritionist (or *PIN*), a prototype system for intelligent nutrition assessment and meal planning. It aims to automate the two main services offered by a nutrition expert, performing human-like: i) patient health state assessment, and ii) meal plan generation. Preliminary results produced based on 16 real-case human test subjects highlight the effectiveness and efficiency of the solution.**

***Keywords*—Nutrition assessment, Nutrition measures, BFP, Meal planning, Fuzzy logic, Transportation problem.**

I. Introduction

At present, establishing a healthy lifestyle has become a very important aspect in people's lives. One of the main requirements of maintaining a healthy lifestyle is a healthy nutrition. Thus, people reach out for a nutrition expert's services, to help achieve this healthy lifestyle requirement. Yet a few obstacles come to mind: i) the cost of seeking an expert's help, and ii) the time commitment required from a person to attend regular meetings with the expert.

To try to solve these issues, we design and develop an intelligent mobile application titled *PIN* (Personal Intelligent Nutritionist) that automates the services offered by a nutrition expert, namely: i) providing the person seeking nutrition advice with an assessment regarding her nutrition-health state: whether she should gain, lose, or maintain her weight (based on different nutrition-health measurements), and then ii) providing her with daily meal plans to meet the optimal nutrition-health state (considering all categories of required nutrients). To achieve this, our solution consists of two main components: i) a *health state assessor* agent specially designed using the fuzzy logic paradigm to evaluate the health state of the user based on various inputs (age, sex, height, weight, and body fat percentage (BFP)), and recommend a target weight and BFP for the user while considering her level of activity and the rate at which the weight change is desired (the agent's final output is the daily caloric intake required to reach the target weight); and ii) a *meal plan generator* agent, designed based on an adaptation of the transportation optimization problem to simulate the "human thought process" involved in generating daily meal plans (based on the health state assessor's output).

In this paper, we aim to highlight *PIN*'s architecture and functionality and discuss its preliminary experimental evaluation. The remainder is organized as follows: section II briefly introduces some health/nutrition related concepts and existing solutions. Section III describes the prototype system's general architecture and its main components. Section IV describes experiments and results, before concluding in section V.

II. Background

A. Nutrition Preliminaries

The first step to perform health assessment is collecting the following input information regarding the patient: i) sex, ii) age, iii) height iv) weight and v) BFP. Next the body mass index (BMI) [1] is calculated as follows:

$$BMI = \frac{Weight(Kg)}{Height^2(m^2)} \quad (1)$$

BMI is an indication of the weight status of a person [1]. Yet as C. Philips demonstrated in his study of 486 subject: "About 39 and 87% of subjects classified as normal and overweight by BMI were obese according to their BFP" [2]. In other words, BMI is not significant by itself and thus the combination of the BMI and BFP allow for a better assessment. In the context of this research, we adopt the BFP classification suggested by the American College of Sports Medicine for different age categories of males and females [3].

After all the required inputs have been provided by the patient the expert nutritionist can decide the goal weight of the patient, and the daily caloric intake required. Weight change comes down to the gap between the caloric intake and the caloric expenditure, meaning the difference between the amount of energy acquired from food and the energy consumed by the human body, both measured in Kilocalories (Kcal). If the daily intake is larger than the daily expenditure the patient will gain weight in the long run, and vice versa [4]. Once the daily caloric intake has been determined, the expert nutritionist can proceed with the second service: producing a daily meal plans for the patient. This can be performed in three main steps: i) based on the daily caloric intake, the expert determines in grams (g) the daily needed amount of the three macro-nutrients: carbohydrates, proteins, and fats [5], ii) based on the needed amount of macronutrients the expert determines the number of servings from the five food categories[1] (starch, fruits, milk, vegetables, lean meat, and fats), and finally iii) the expert will select the food items for each food category, from the list mentioned above, to meet the required number of servings and then organize the food items throughout the days of the week.

B. Existing E-Solutions

Applications related to health are becoming more and more available for users on different platforms. Companies such as Google, Microsoft and others are contributing in the field through different applications and wearables. One such solution is MyFitnessPal [6] which accepts as input: health state information from the user (namely: sex, age, height, weight, and level of activity) as well as the user's destination weight, and produces as output: the required number of calories per day and the distribution of micro-nutrients necessary to reach the destination weight. It also offers additional functionality related to training and workout logs. Yet, MyFitnessPal does not set up meal plans, and basically acts as a calorie counter for the user without displaying any significant intelligent behavior. Another solution is EatThisMuch [7] which accepts as input: basic health state information from the user (e.g., sex, age, height, weight, and level of activity, similarly to MyFitnessPal) in addition to the BFP. It also accepts as input the user's destination weight in textual from (i.e., maintain weight, lose weight, gain weight, and gain muscle), the user's preferred diet type (e.g., mediterranean,

[1] Adopted based on the *Diabetic Exchange List* suggested by the American Dietetic Association [1].

vegetarian), as well as her food preferences (i.e., whether the user wants a food item to appear or not in her daily mean plans). The application then produces as output daily meal plans. While powerful, yet this solution has a few limitations: i) allowing the user to generate meal plans for the current day only (planning ahead required premium subscription), ii) considers user preferences in an "*include*" or "*do not include"* crisp fashion (rather than allowing a gradient rating of food preferences, e.g., ∈[0, 1] from "*not preferable*"–to–"*highly preferable*", which would much more useful in producing adapted meal plans), iii) considers BFP in a non-numeric form, which inherently allows for a less accurate evaluation of the user's health state, and iv) does not make any decision regarding the health state of the patient (it does not generate a user destination weight). Fitness Meal Planner [8] is yet another online application sharing most of the limitations of the latter solution.

The authors in [9] develop a tool to monitor foods consumed by the user, using food image recognition and machine learning to provide nutrition analysis. Yet the nutrition analysis process is not fully automated since the user is required to provide prior (expert) knowledge about the nutrition analysis data. In [10], the authors introduce a machine learning algorithm called Multi-Armed Ban (MAB) to cluster the physical activities and food logs of the user, and provide personalized suggestions such as recommended meals or increasing the user's physical activity. Yet, similarly to [9], the solution is not completely automated and requires the user's involvement in the different stages of the evaluation process. Few knowledge-based approaches have been developed, e.g., [11, 12, 13], using food ontologies constructed by domain experts, coined with fuzzy inference rules, to evaluate meal plans. Yet, most approaches in this category focus on evaluating existing meal plans suggested by the user, rather than performing automatic meal plan generation.

To sum up, most existing solutions share the following weaknesses, namely: i) a lack of a completely automated process for health assessment and meal planning, ii) providing coarse health assessments considering using basic indicators (such as gender and weight) rather than using more formal nutrition measurements such as BFP and BMI which would naturally allow more accurate assessments, and iii) using pre-defined meal plans with limited adaptability with respect to user preferences. We address all the above limitations in our PIN solution.

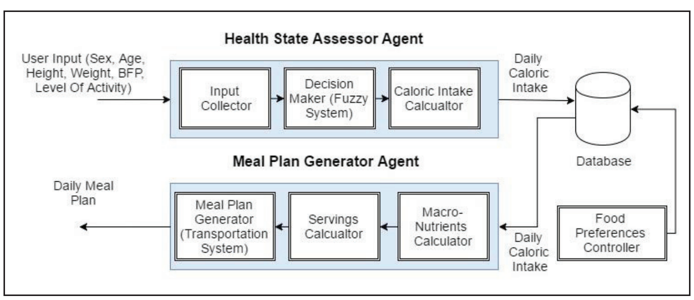

Fig. 1. Overall PIN architecture

III. Solution Design

A. Overall System Architecture

Our solution aims to automate the health assessment and meal plan recommendation services offered by a nutrition expert. The general architecture of our solution is shown in Fig. 1. The user interacts with the prototype system using two interfaces dedicated to both the health state assessor and meal plan generator agents. Initially the user interacts with the health state assessor agent to undergo an assessment and determine her destination weight and BFP. Once the assessment is completed, the user would then interact with the meal plan generator, choosing food preferences through a dedicated controller, before the system starts generating meal plans. Note that the user can also interact with both agents at any time and any order to re-assess her health state and/or generate new plans.

B. Health State Assessor (HSA) Agent

As shown in Fig.1, the health state assessor agent consists of three main components that behave in a sequential fashion in order to automate the health assessment process:

Component 1: ***Input collector***, which collects patient information as illustrated in section II.

Component 2: ***Decision maker***, i.e., a fuzzy logic agent performing common sense decision making based on both the BMI and the BFP. This component was designed using the fuzzy logic paradigm to evaluate the health state of the patient and produce the target BFP from which the target weight can then be produced. The overall fuzzy process is described in Fig. 2.

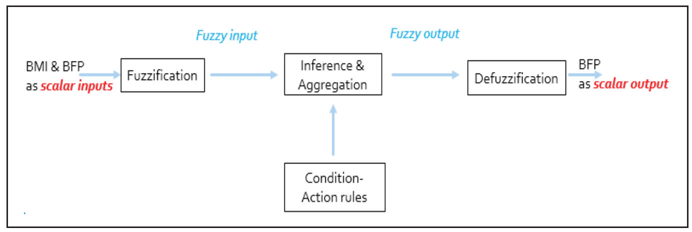

Fig. 2. Health state assessor's fuzzy logic process

The fuzzy partitions of the BMI are shown in Fig. 3. We carefully crafted the latter following the World Health Organization BMI crisp value classification [1]. We crafted similar BFP fuzzy partitions based on the American Dietetic Association's BFP crisp classification [4]. All fuzzy partitions are available online[2]. A set of dedicated condition-action rules were also carefully crafted in order to highlight proper and healthy BMI state transitions. *Mamdani's* approach (cf. formula 2) was adopted as the inference function, *Maximization* was adopted as the aggregation function, and the *Center of Gravity* (cf. formula 3) was adopted as the defuzzification function (other functions could have been used [14]).

$$P1 \Longrightarrow P2 \quad \equiv \quad P1 \wedge P2 \tag{2}$$

$$X = \frac{\int X * F(X) * dX}{\int F(X) * dX} \tag{3}$$

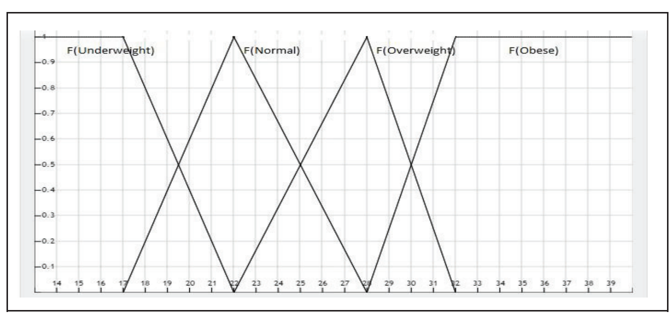

Fig. 3. BMI fuzzy partitions

Note that there is no algorithmic method to compute BFP. Our literature review and discussions with professional nutritionists

[2] http://sigappfr.acm.org/Projects/PIN/

indicate this is a "fuzzy" task by nature, which usually relies on the experience and expertise of the nutritionist; hence our adoption of the fuzzy logic paradigm to address this task.

Component 3: ***Caloric intake calculator***. Once all inputs are acquired and the target weight is determined, the daily caloric intake is straightforwardly calculated following a deterministic mathematical process adopted in the literature [1].

C. Meal Plan Generator (MPG) Agent

The meal plan generator agent consists of three main components. Similar to the health state assessor agent, the components behave in a sequential fashion in order to automate the meal plan generation process:

Component 1: ***Macro-nutrient calculator***. It calculates the amount of macro-nutrients (carbohydrates, proteins, fats) in grams, based on the daily caloric intake produced by the *HSA* agent.

Component 2*: Servings Calculator*. It produces the daily amount of servings for the six primary food categories adopted in our study (i.e., starch, fruits, milk, vegetables, lean meat, and fats) based on the amounts of macro-nutrients produced by the micro-nutrient calculator.

Component 3: ***Meal Plan Generator***. This component is designed based the transportation optimization paradigm [15, 16] to allocate food items to the five daily meals (i.e., breakfast, snack 1, lunch, snack 2, and dinner) to meet the servings requirements. First the number of servings is distributed over the five meals. Consequently, the meal plan generation process comes down to solving five different transportation matrices for the five different food categories where: i) the supply represents the available amount of food items per food category, ii) the demand represents the number of servings per food category for every meal, and iii) the cost represents the inverse of the likelihood of a food item being associated with a meal. For instance, Fig. 4 shows the transportation model for the fruits category, where every food item is linked with every meal with a cost: *C* (*supply*, *demand*). The cost is evaluated as the linear combination (weighted sum) of three cost factors: i) a prefixed cost based on experts' recommendations, ii) user preferences, and iii) updated costs that act as a memory to avoid repetitive occurrences of food items from day-to-day and then render the meal plans more dynamic. The transportation problem is then solved using the *Least Cost Cell Method* [10, 11] in order to match the food servings for every meal (demand) with the available food items (supply).

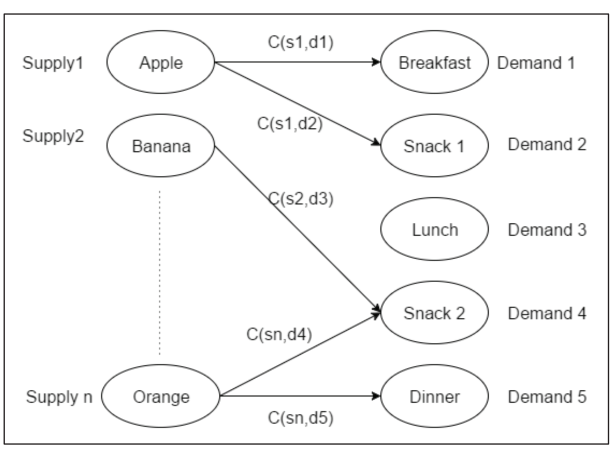

Fig. 4. Sample transportation model for the fruits food category

IV. Experimental Evaluation

In order to achieve all functional and non-function requirements discussed previously, we implemented our prototype system as a light-weight android (mobile) application [3], using methods of the *jFuzzyLogic* open source library [17, 18] in implementing our fuzzy logic *HSA* agent and developing our own implementation of the transportation problem to build our *MPG* agent. We have empirically tested the different components of our system, namely: i) the similarity between destination weights and BFPs suggested by *HSA* agent compared with the nutrition experts' recommendations, ii) the correctness of the recommendations of the *HSA* agent, as well as iii) the correctness of the meal plans generated by the *MPG* agent.

A. Experimental Test Data

A group of 4 nutrition experts and 16 patients (7 female and 9 male) participated in the experimental evaluation process. Patients were carefully chosen among cases treated by our target nutrition experts in order to cover different spans of: age (∈[22, 59] with avg=33.82 and stdv=11.49), weight (∈[52, 121.5] kg, with avg= 76.52 kg and stdv=16.67 kg), BFP (∈[7, 46.2]% with avg = 26.27% and stdv = 12.19 kb), and BMI (∈18.8, 39.5] with avg = 26.39 and stdv = 4.61).

B. Destination Weight and BFP Evaluation

As a first step in evaluating the results of our solution, the weights and BFPs recommended by the nutrition experts where compared with those of our system's *HSA* agent. The results where compared using Pearson's Correlation Coefficient (PCC) where x and y designate the average experts' weights (BFPs) and the system's weights (BFPs) respectively, σ_x and σ_y designate their standard deviations, and δ_{xy} their co-variance:

$$pcc = \frac{\delta_{xy}}{\sigma_{x^*}\,\sigma_y} \qquad (4)$$

Tables 1 and 2 respectively show the correlation between the expert and the software's recommended weights and BFPs.

Table 1: Testers' and system's destination weight correlation

	Software – Testers				
Software/tester pair	Tester 1	Tester 2	Tester 3	Tester 4	Avg.
Destination body weight correlation	0.9507	0.8945	0.8469	0.9786	0.9447

Table 2: Testers' and system's destination BFP correlation

	Software - Testers			
Software/tester pair	Tester 1	Tester 2	Tester 3	Avg.
Destination BFP correlation	0.8343	0.7936	0.9173	0.8871

Based on Table 1, *PIN*'s *HSA* agent scores a minimum correlation of 84.69% with tester 3, and a maximum of 97.86% with tester 4, while scoring a remarkably high average correlation of 94.47% considering the average destination weights recommended by all four nutrition experts. Similarly in Table 2, BFP correlation levels were remarkably high, reaching an average value of 88.7 % agreement with the nutrition experts' BFP recommendations.

Recall that there is no algorithmic method to compute destination BFP levels. Professional nutritionists rely on their experience and expertise to provide such recommendations.

[3] Available online at: http://sigappfr.acm.org/Projects/PIN/

C. Health State Assessor (HSA) Agent Evaluation

We conducted a dedicated experiment to allow human experts to evaluate our *HSA* agent's assessment process. For each of the 16 patient cases considered in our study, each of our 4 nutrition experts was provided with the system's *HSA* evaluation and was asked to rate it on grade scale from 1-to-4, where 1, 2, 3 and 4 are associated with strongly disagree, disagree, agree, and strongly agree respectively. Results are compiled and shown in the Fig. 5.

Based on results in Fig. 5, 31.2% of the system's evaluation scored an average grade of 3.5/4 or above, with a minimum grade of 2.5/4. The grades are fairly satisfying, yet they also show that there's still room for improvement in terms of: the relationship between the target body weight on one hand and target BFP on the other hand.

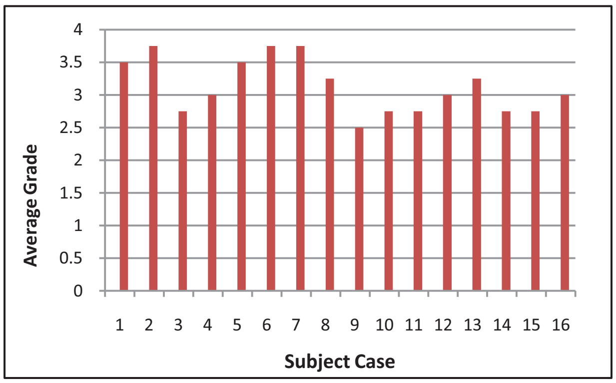

Fig. 5. *HSA* agent average ratings for all 4 experts

D. Meal Plan Generator (MPG) Agent Evaluation

Another main objective of our proposed solution is to generate meal plans that fulfill the user health requirements. Hence, similarly to our *HSA* evaluation, we presented to the nutrition experts with four three-day meal plans generated by our system's *MPG* agent, and asked the experts to rate them. The meal plans were evaluated in terms of three criteria: i) whether a meal plan provides the needed macronutrients, ii) whether food items are correctly assigned to every meal, and iii) whether a meal plan has food variety. The criteria where evaluated on grade scale from 1-to-4, from strongly disagree to strongly agree respectively. Four caloric intake cases were considered (1200 Kcal, 1500 Kcal, 1800 Kcal, 2100 Kcal). Results, compiled in Fig. 6, are clearly satisfying and show that experts mostly strongly agree with our solution's meal plan suggestions, especially in terms of providing the needed nutrients and food items assignments. Yet, further enhancements could be made to improve food item variability in every meal plan (considering for instance the available food items). Note that we have also evaluated our solution's time and memory performance: decisions are made almost instantaneously, in less than 40 milliseconds, whereas storage memory does not surpass 15 MB.

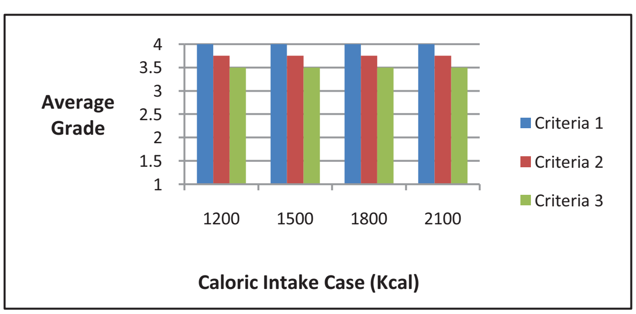

Fig. 6. *MPG* agent average ratings for all 4 experts

V. Conclusion

This paper briefly describes *PIN*: a computerized solution for Personalized Intelligent Nutrition recommendations, including two main aspects: i) determining the health state of a patient and providing a recommendation accordingly regarding her weight and BFP, and ii) recommending meal plans to ensure the patient's healthy transition toward her target weight. The solution is original in combining two paradigms: fuzzy logic and the transportation optimization problem, in order to provide weight/BFP and meal recommendations respectively. The design was implemented as a light weight portable android application, and was evaluated on 16 real patient cases with the help of 4 nutrition experts.

In the oral demonstration of *PIN*, we aim to showcase the prototype system's logical design, implementation, and functionality, highlighting the different system parameters and their impact w.r.t. the patient cases being tested. We will also present and discuss our latest experimental evaluation and results, highlighting the system's effectiveness and efficiency, as well as its strong and weak points in producing health assessments and meal recommendations, emphasizing ongoing design and technical improvements.

As ongoing works, we are currently investigating statistical features to track the application user's progress in both weight and BFP changes, and then update assessments and recommendations accordingly. A future functionality would be to accept as user input the supply of available food, and then update meal suggestions accordingly. Also, another future direction is to consider the user's profile (her lifestyle and the kinds of physical activities she does) to infer her health state and update recommendations accordingly.

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