Nutrition Counseling System and Food Menu Planning

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Abstract— **In recent years the effects of industrial growth have resulted in drastic changes in consuming behavior, standard of living, and lifestyles. In particular there has been a significant rise in the number of people who eat out regularly. This often means that they cannot control the characteristics of the food they take, such as its taste, calories per portion, and other nutritional details. As a result they may become prone to obesity. Today people are confronted with more difficult decisions about how to select food items suitable to their nutritional needs. In this paper, we present a new nutrition counseling system for food menu planning (NCS). This NCS not only assists in finding the appropriate menu for users, by entering data parameters such as gender, age, height, weight, exercise activity and favorite food but also provides meals customized to each individual nutritional profile. In the near future such systems might become integral to an encompassing lifestyle health information system.**

Keywords-component; nutrition counseling system; food menu planning; NCS; K-means clustering

I. INTRODUCTION

With accelerating economic growth in major capital cities such as Bangkok, Thailand, most people engaged with demanding workloads have developed fundamental changes in their eating' habits. There is a tendency to eat out or snack, and often those foods are less nutritious. Coupled with the fact that there is an inclination to adopt more sedentary lifestyles, obesity can occur when daily caloric intake surpasses daily bodily demands. One reason is that consumers cannot control the cooking method, tastes, and nutritional characteristics per serving. There is a need for the NCS to offer healthier menu suggestions catered to individual preferences. Previously, researchers have designed a few expert or intelligent systems in order to deal with this issue. Lee et al. proposed "An intelligent Healthcare Agent for Food Recommendation at Tainan City", Taiwan [1] but we have realized that the quantity of calories daily that people should consumed is unknown. In addition, they proposed "Intelligent Ontological Agent for Diabetic Food Recommendation" [2] which counseled only dinner menus based on fixed breakfast and lunch menus.

Food clustering is a procedure used to identify attribute similarities between different foods. If comparable foodstuffs are allotted to the same cluster then one can replace certain foods of similar characteristics in order to avoid generating the same monotonous dish or menu suggestions each time. Li et al. proposed "Food clustering Analysis for Personalized Food Replacement" [3], and "Automate Food Ontology Construction Mechanism for Diabetes Diet Care" [4]. These two methods represent the level of nutrition of food items as high, medium, and low. However, this scaling is not sufficiently fine enough to generate variable food menu suggestions.

The NCS described in this study possesses additional functions over its predecessors because of its ability to propose menus for local Thai mixed food dishes as well as one-plate dishes for three meals (breakfast, lunch, and dinner) that meet most personal tastes. Besides, each user will be informed of how many calories, protein, fats and carbohydrates will be or should be consumed.

This NCS is designed to perform two functions: 1) to propose a food menu for three meals (breakfast/lunch/dinner) that users may be interested in based on their dietary preferences and 2) to support users during the selection of a menu that best matches their nutritional requirements.

The rest of this paper is organized as follows. Section II describes the essential nutritional constituents selected for the NCS. Section III describes the materials and methods. The experimental results, discussion and limitations are presented in sections IV and V respectively. Finally, potential future developments and a summary are stated in section VI.

II. THE ESSENTIAL NUTRIENAL CONSTITUENTS SELECTED FOR THE NCS

Mckinley describes essential nutrition for survival from a nutritionist's health care viewpoint [5].

a) Energy: The energy used for the human body to work properly. The amount of energy in a food depends on the amount of calories from such food. The amount of energy required also depends on age, height, weight, gender, and

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activity level. People who consume calories in excess of daily utilization can become overweight.

b) Carbohydrates: The macronutrients needed the most. Based on "Dietary Reference Intakes" published by the United States Department of Agriculture (USDA), around 50% of calories come from carbohydrates. There are many reasons why carbohydrates are very important for human body and they are as follows:

- The main source of energy in human' body is carbohydrates.
- The central nervous system, the heart, the brain, and the muscles use carbohydrates to function correctly.

Carbohydrates are mostly found in starchy foods, fruits, milk, and yogurt. Some foods contain low carbohydrates such as vegetables, beans, nuts, seeds and cottage cheese.

c) Protein: With reference to the USDA's, "Dietary Reference Intakes", a small amount of calories come from protein, for which, most of people get this kind of nutritional need sufficiently. People require protein because:

- Growth (In particular, chiefly influential for children, teenagers, and pregnant women)
- Repairing other cells.
- Body immune system.
- Producing mainly enzymes and hormones
- Being energy when carbohydrate is not available

Protein is found in fish, meats, meat substitutes, poultry, cheese, nuts, legumes, milk, and in lower quantities in starchy vegetables.

d) Fats have been portrayed as the main culprit for causing obesity and therefore have a poor reputation. However some fats are essential for survival. According to the USDA, "Dietary Reference Intakes" one-third of calories come from fats. Fats are required for:

- Growth
- The most concentrated source of energy by fats
- Taking care of all cell membranes

Fats are found in lard, oil meat, milk products, butters, poultry and margarines, grain products and salad dressings, and fish were found fats.

III. Materials and Methods

A. Food database

This study is based on the database provided from the Inmucal-Nutrients program, Institute of Nutrition, Mahidol University, Thailand [6]. Table 1 depicts the fact that considerable differences between foodstuffs within the same group in terms of the quantity of vital nutrients exist.

B. Method

This study proposes the NCS and its corresponding processing methods are shown in Fig. 1.

Phase 1: Preprocess Data

In the raw data, the notation "-", "Tr" and "0" represent that the nutrients are either not inspected for, of negligible values, or incapable of detected by the equipments respectively. Under those terms, the study defaults the value to be "0".

TABLE I. Illustration of the Processed Raw Data

ID	Foodname(en)	Amount	Unit	Energy (Kcal)	Protein (g.)	Others
72001	Rice with chicken green curry	1	MI	460.80	21.12	…
71001	Rice with pig leg with gravy / Khao ka-moo (Thai)	1	MI	497.15	21.96	…
74001	Rice with shrimp paste / Khao kluk kapi (Thai)	1	MI	597.13	26.60	…
71002	Rice, fried with pork, vegetable, and egg	1	MI	489.24	19.12	…
71003	Rice with red pork + Roasted red pork dipping sauce	1	MI	634.41	19.75	…
74002	Fried rice with egg	1	MI	592.89	10.56	…
71004	Khao moo krob (Thai)	1	MI	537.25	22.41	…
72004	Khao man kai tod (Thai)	1	MI	653.73	24.34	…
74003	Khao na ped yang (Thai)	1	MI	408.31	15.96	…
74005	Rice+egg in five spices soup / Khao rad khai palo (Thai)	1	MI	582.40	18.24	…
71005	Rice+fried seasoning pork / Khao moo-tod (Thai)	1	MI	442.08	23.64	…
74006	Khao-mun somtum (Thai)	250	GR	440.00	12.31	…
84001	Cooked fish maw	1	MI	306.27	26.94	…
84002	Fried rice noodles, Thai style	1	MI	677.82	22.02	…
81001	Rice noodle, small size, with pork	1	MI	470.25	17.78	…
84003	Wide rice noodles with pork, egg and soysauce	1	MI	630.50	20.48	…
84004	Wide rice noodles with fish ball, swamp cabbage	1	MI	319.50	12.60	…
84007	Fermented rice noodles with peanut curry	1	MI	498.68	11.28	…
84008	Fermented rice noodles with fish curry	1	MI	265.72	13.10	…
84009	Fermented rice noodles with fish curry, Southern style	1	MI	309.40	14.20	…
84010	Kuay tiew num ped (Thai)	1	MI	305.20	17.00	…
84011	Noodle sheets, soup with meat and tofu / Guay-jub (Thai)	1	MI	290.64	15.92	…
84012	Rice noodles with beef curry / Guay-teaw khak (Thai)	1	MI	497.80	25.08	…
81002	Rice noodles, topped with minced beef in gravy	1	MI	365.12	11.41	…
81004	Wheat noodle / Ba-mee (Thai), with roasted pork	1	CU	337.26	11.97	…
84015	Rice noodles, small size, with beef and soup	1	MI	335.72	20.06	…
84018	Rice noodles, small size, with beef ball	1	MI	344.25	12.38	…
84019	Rice noodles, fine thread, with stewed beef	1	MI	348.80	23.54	…
84020	Rice noodles, fine thread, with beef and soup	1	MI	313.92	19.18	…
84022	Rice noodles, fine thread, with beef ball and soup	1	MI	235.00	15.04	…
84023	Rice noodles, fine thread, with beef ball, beef and soup	1	MI	310.20	22.56	…
84025	Rice noodles, fine thread, with beef ball	1	MI	342.00	13.28	…
84026	Rice noodles, big size, with beef ball and soup	1	MI	286.70	21.62	…
84028	Rice noodles, big size, with beef ball, beef and stewed beef	1	MI	364.50	17.33	…
81005	Rice noodles, big size, with pork and soup	1	MI	340.08	30.96	…
81006	Macaroni, fried with pork	1	MI	536.25	18.53	…
84029	Thai fried noodle (Pad Thai) (Fat 6 %)	1	MI	440.44	18.30	…

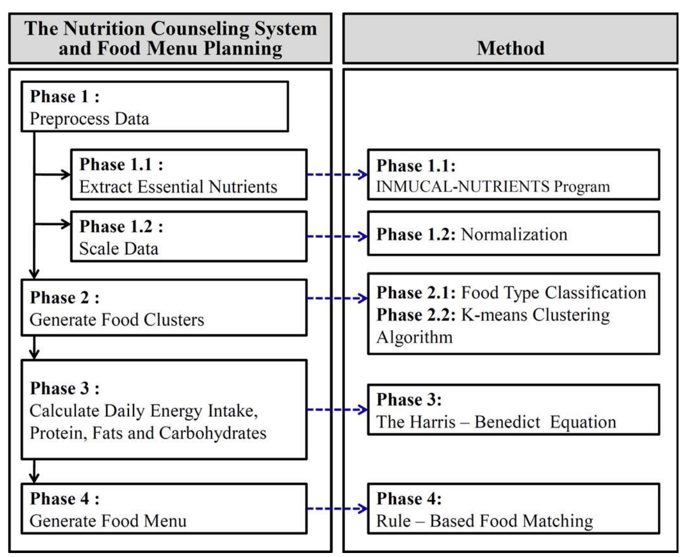

Figure 1. Nutrition counseling framework and corresponding methods.

a) Phase 1.1: Extract the Essential Nutrients by using Inmucal- Nutrients program

Inmucal-Nutrients program was developed by the Institute of Nutrition, Mahidol University, Thailand. The program allows one to input the food ingredients and then it calculates the nutrition values, which are, energy, protein, fat and carbohydrate, of each dish. We has adopted this program and adapted it to become the database for the NCS.

b) Phase 1.2: Scale Data – Normalization

A normalization technique [7] used in this paper is for transforming the value of each nutritional feature into a range of 0 and 1. Suppose the nutritional feature is in the range of possible minimum and maximum value as [$value_{\min}$ $value_{\max}$] and not in the range of [0, 1]. Then now the range of value should be transformed into the range of [0, 1].

Define that the notation *value* and δ are the original value and the normalized value, respectively. If the maximum and minimum values are known, then normalization can be done by using (1).

$$\delta = \frac{\text{value}}{\text{value}_{\max}} \tag{1}$$

This method yields the normalized value within the range of [0, 1]. If $value = value_{min}$, then $\delta = 0$. If $value = value_{max}$, then $\delta = 1$. For example, the foodstuff named "rice porridge with pork" that possesses the characteristics of nutrition energy, protein, fats and carbohydrates as 217 kcal, 14 gram, 4 gram, 31 gram, respectively. After normalized process, then the values become 0.3483, 0.2778, 0.1507 and 0.4002, respectively. All raw data is first normalized before entering Phase 2.

Phase 2 : Generate Food Clusters

a) Phase 2.1 : Food Type Classification

The database was manually grouped into 5 major categories: 1) Breakfast, 2) Main dishes, 3) Dessert & Fruits, 4) Snacks and 5) Drinks, which are composed of totally 836 foodstuffs. The code settings for each category are described below:

- "Breakfast" group code: 90000.
- "Main dishes" group code: 60000 for food set, 70000 for mixed food, and 80000 for noodle.
- "Dessert & Fruits" group code: 54000 for dessert and 55000 for fruit.
- "Snack" group code: 44000
- "Drink" group code: 52000

For "Breakfast", "Main dishes", and "Snack" groups the second digit of the code is set to 1,2,3,4 representing the preference or favorite ingredient as "1 means pork", "2 means chicken", "3 means seafood" and "4 means others". For instance, Code 62013 is this main dish (food set) made from chicken ranging no. 13 and Code 73001 is this main dish (mixed food) made from seafood ranging 1.

b) Phase 2.2 : A silhouette value and K-means clustering algorithm

After food type classification, a second tier clustering by using a K-means clustering algorithm is then performed. Before starting K-means clustering, we would like to present an important factor, namely, silhouette value [8,9]. A silhouette plot is created using the cluster indices output from the K-means. The plot depicts a measure of how close each point in one cluster is to points in the neighboring clusters. This measure ranges from +1, indicating points that are very distant from neighboring clusters, through 0, indicating points that are not distinctly in one cluster or another, to -1, indicating points that are probably assigned to the wrong cluster. It is defined by the follow construction (2).

$$s_i = \frac{\min\limits_{(K)} \beta_i^{(K)} - \alpha_i}{\max[\min\limits_{(K)} \beta_i, \alpha_i]} \tag{2}$$

where $\alpha(i)$ is the average distance from the i th point to the other points in its cluster, and $\beta(i,k)$ is the average distance from the i th point to points in another cluster k.

This study tried to cluster from $k = 4$ to $k = 10$, in order to know what k indicated the mean highest silhouette value (Table II).

TABLE II. COMPARISON MEAN-SILHOUETTE FROM $K = 4$ TO $K = 10$ OF EACH FOOD TYPE CLASSIFICATION

Food type classification (→) Cluster (↓)	Maindish	Dessert	Drinks	Snacks	Breakfast
k=4	0.5755	0.6160	0.6465	0.6121	0.5058
k=5	0.5915	0.5847	0.7190	0.5478	0.4471
k=6	0.5714	0.5851	0.5534	0.4840	0.4606
K=7	0.4646	0.5755	0.5405	0.5047	0.4071
k=8	0.5427	0.5859	0.6776	0.3980	0.3697
k=9	0.5144	0.5158	0.5363	0.4709	0.4298
k=10	0.5416	0.5372	0.6854	0.4349	0.3702

For example, the "Drinks" group got mean-silhouette value = 0.7190 or 71.90 % at $k = 5$, the "Maindish" group got mean-silhouette value = 0.5915 or 59.15 % at $k = 5$, the "Dessert" group got mean-silhouette value = 0.6160 or 61.60 % at $k = 4$, this is the optimal k that achieves the mean maximum silhouette value as illustrated in Fig. 2.

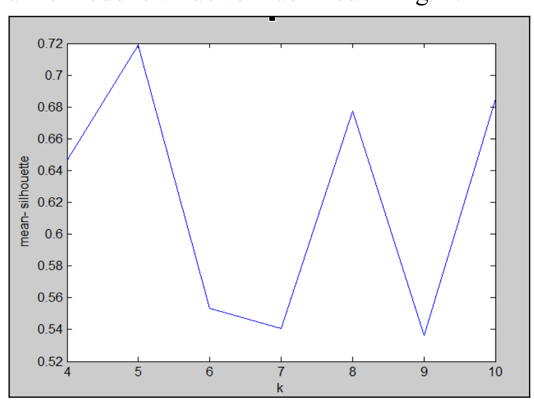

Figure 2. Mean-silhouette values of "Drinks" group with respect to the number of clusters. Mean-silhouette value is 0.7190 or 71.90% when k is 5.

Table III shows a silhouette value of each 77 menus in "Drinks" group such as "Passion fruit juice" stays in cluster 1 (the correction of 71.29 %) and "Coffee with sugar and milk added, hot/ice (Burdy), ready to drink" stays in cluster 5 (the correction of 91.41 %).

TABLE III. AN EXAMPLE OF A SILHOUETTE VALUE OF EACH 77 MENUS IN "DRINKS" GROUP

Drinks Menu	Silhouette value
Sugarcane juice, fresh	0.2945
Toddy palm, juice	0.8713
Orange juice	0.6520
Fanta Orange	0.8149
Coca-Cola	0.3977
Tomato juice	0.7970
Pinapple juice, fresh	0.5362
Pineapple juice, canned	0.8482
Red grape juice 100%	0.8682
Lychee juice 25%	0.8947
Passion fruit juice, 25%	0.0054
Guava red juice, 25%	0.8816
Roselle drink	0.6224
Soybean milk (with milk powder), UHT	0.9669
Apple juice 100% (Malee brand)	0.8986
Orange juice, 100%	0.8878
Coconut juice	0.3130
Aloe vera drink, flavoured	0.6046
Mature coconut, water	0.8080
Soybean milk, vegetarian formula no suger	0.9107
Passion fruit juice	0.7129
Refreshment beverage (Sponsor)	0.8671
Energy drink (Karabaow dang)	0.1153
Tea, hot/ice (no sugar added), ready to drink	0.7746
Tea with sugar added (hot tea/ice black tea), ready to drink	0.8931
Milk tea, hot/ice, ready to drink (sugar 9%)	0.4003
Coffee with sugar added, hot/ice (O-laing), ready to drink	0.8931

Generally, the algorithm of K-means clustering [10, 11, 12] is the simple unsupervised learning algorithm. The procedure classifies a given data set through a certain number of clusters (assume *k* clusters) fixed a priori. The cost function is shown as follows [13, 14, 15]:

$$\rho = \sum_{j=1}^{k}\sum_{i=1}^{n}\left\|x_i^{(j)} - c_j\right\|^2 \tag{3}$$

where $\left\|x_{ji} - c_j\right\|^2$ is a chosen distance measure between a data point x_{ji} belonging to cluster j and a center of cluster c_j. The algorithm is summarized as the flowchart in Fig. 3.

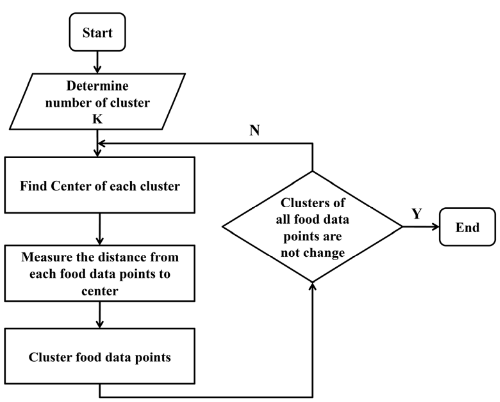

Figure 3. K-means clustering algorithm.

From the K-means clustering algorithm, assume that there are five clusters of "Drinks" group (*k* is five because the mean-silhouette value gains the highest), After the K-means analysis, the results are shown in Fig. 4 which is described as follows: all foodstuffs in five clusters, in which the fourth and fifth clusters contain a small number of data points, have a high silhouette value that greater than 0.7, which means good separate because there are no negative values. In addition, most of foodstuffs are stated in the first cluster because of the similarity of each nutritional feature.

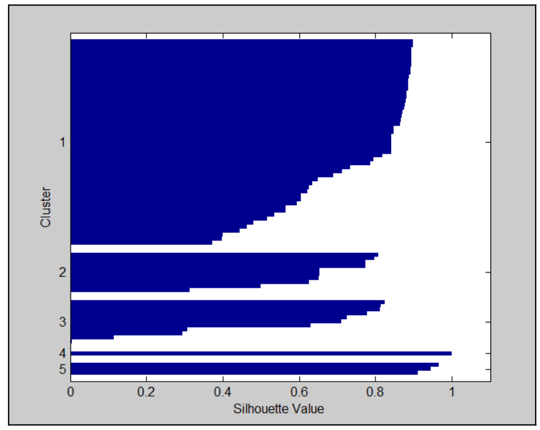

Figure 4. An example of "Drinks" group of exploring possible clustering in four-dimensional data foodstuffs corresponding to four nutrients with five clusters.

However, in the "Desert & fruit" group, the first, second and third clusters contain many points with positive silhouette values, but some remain negative. This indicates that some foodstuffs are not well categorized into the wrong cluster as shown in Fig. 5.

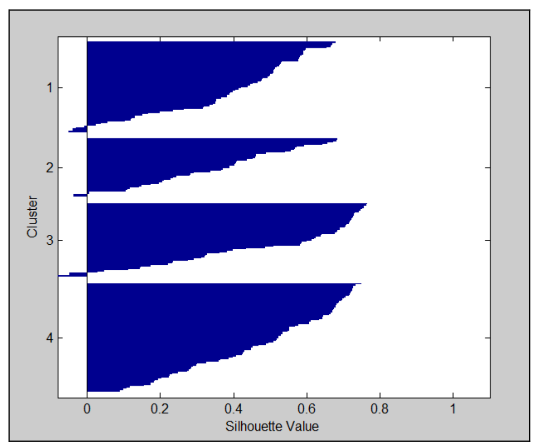

Figure 5. An example of "Dessert & fruit" group indicated that somewhere with negative values silhouette.

The weakness of this algorithm is that it is significantly sensitive to the initial randomly selected cluster center.

Phase 3: Calculate daily energy intake, protein, fats and carbohydrates – The Harris-Benedict equation

We use the Harris-Benedict equation [16], listed in Table IV, to compute the basic energy requirement based on individual parameters such as gender, height, weight, age and exercise activity. Firstly, users plan the daily quantity of calories needed using the equation. Then, the NCS multiplies this by a factor of 1.2~1.9 to response for excessive energy requirement related to individual weekly activity. Table V lists the counseled percentage of the daily intake for protein, fats and carbohydrates.

TABLE IV. THE HARRIS-BENEDICT EQUATION

Gender	Basal Metabolic Rate (BMR) - measure in kcal.
Female	655+(9.6xWeight)+(1.8xHeight)-(4.7xAge)
Male	66 + (13.7xWeight)+(5xHeight)-(6.8xAge)

TABLE V. COUNSELED PERCENT OF THE DAILY INTAKE FOR PROTEIN, FATS AND CARBOHYDRATES

Nutrient	Percentage of total daily calories (%)
Protein	12-20
Fats	25-35
Carbohydrates	55-65

The nutrition users need per person per day has to be sub-categorized into protein, fats and carbohydrates. The counseled individual daily intake should be: 13% of protein, 30% of fats, and 57% of carbohydrates [17]. This is an advising for an average person from the general population. Significant differences may exist because of some factors such as whether person has diabetes mellitus.

Phase4: Generate Food Menu – Rule-Based Food Planning

After obtaining data from the food clustering analysis and by adopting the Harris-Benedict equation one could the proceed with food menu planning. We created a food menu planning framework with daily meals weighting as follows: 35% "Breakfast", 35% "Lunch" and 30% "Dinner". The weighting process took into account the properties and categorical combination of each meal. To further elaborate, the properties mean the nutritional content (energy, protein, fats and carbohydrates) and the categorical combination refers to which categories of the major 5 categories of each foodstuff belong to. This will aid users to establish their most suitable food menus. In order to further achieve this purpose, we designed the program to allow the user to specify some other restrictions (personal preference and nutrition advised) to customize the results. The algorithms are composed of the following steps as shown in Fig. 6.

IV. EXPERIMENTAL RESULTS

The NCS was performed with Matlab and the experiment recruited eight end users. The users' profiles are given in Table VI. All of the food information was collected from the Inmucal-nutrition program. This included 256 "Breakfast" items, 209 "Main dish" items, 190 "Dessert and fruit" items, 90 "Snack" items, and 91 "Drink" items.

For example, user 1 is considered. He entered his profile in the NCS as shown in Fig. 7. He also gave a self-estimated weekly exercise activity level rating. Sedentary users, for example office workers, may have very little exercise and might rate themselves as "1". Manual laborers or professional athletes will likely rate themselves as having heavy exercise levels i.e. "5". Next, the screenshot of user 1's preference will show up and require user 1 to answer personal preference questions such as "Do you like pork, chicken, seafood?" (Fig. 8) one can type *y* (meaning yes) or otherwise type *n* (meaning no), then check "OK". The end user is then required to answer further questions as follows: "Enter no. of menus you want to generate (Fig. 9)" meaning how many menus the system should generate for the user. After a short period of time, the NCS will both display users 1's nutritional needs (Fig. 10) and a detailed food menu suggestion (Table VII).

Ultimately, the decision to follow the generated food menu suggestions rests with user. The NCS is only a guide to help people in making these important decisions.

Database Creating Algorithm

begin

1. Collect five categories of food database and calculate their nutrition.
2. Use significant nutritional content as features for clustering using K-means clustering method.

End

Menu Generating Algorithm

Let variables used for calculation be as follows:

AG: accumulative nutrition got during a day
TN: total nutrition needed in a day
BG: breakfast nutrition got
BN: breakfast nutrition needed
MSG: morning snack nutrition got
MSN: morning snack nutrition needed
LG: lunch nutrition got
LN: lunch nutrition needed
ASG: afternoon snack nutrition got
ASN: afternoon snack nutrition needed
DG: dinner nutrition got
DN: dinner nutrition needed

begin

1. Input personal information to calculate individual all-day nutrition needed (TN).
2. Calculate nutritional content needed for each meal.
3. Generate breakfast menu achieving BG by selecting from the food cluster which its center is close to BN. Then,
   $$AG = BG$$
4. If $BG < BN$, apply
   $$MSN = BN - BG$$
   - Generate morning snack menu achieving MSG from the food cluster which its center is close to MSN.
   - Calculate
   $$AG = AG + MSG$$
5. Calculate LN using the following equation
   $$LN = 0.7\ TN - BG - MSG$$
   where 0.7 is a portion of daily calories for two first meals.
6. Generate lunch menu achieving LG by selecting from the food cluster which its center is close to LN. Then,
   $$AG = AG + LG$$
7. If $AG < 0.7\ TN$, apply
   $$ASN = 0.7\ TN - AG$$
   - Generate afternoon snack menu achieving ASG from the food cluster which its center is closet to ASN.
   - Calculate
   $$AG = AG + ASG$$
8. Calculate DN using the following equation
   $$DN = TN - AG$$
9. Generate dinner menu achieving DG by selecting from the food cluster which its center is closet to DN. Then,
   $$AG = AG + DG$$

end

Figure 6. Proposed algorithm for the NCS.

TABLE VI. THE USERS' PROFILES

USER	SEX	AGE (YEARS)	HEIGHT (Cms.)	WEIGHT (Kgs.)	PREFERENCE	SELF-ESTIMATED EXERCISE ACTIVITY PER WEEK
1	Male	49	176	61	Anything, Not seafood	Moderate
2	Male	31	170	66	Anything	Very – Heavy
3	Female	60	158	65	Anything, Not chicken	Little
4	Male	26	167	80	Pork	Little
5	Female	18	153	55	Pork	Light
6	Female	22	160	60	Seafood and others	Light
7	Female	28	155	58	others	Moderate
8	Male	52	164	55	others	Light

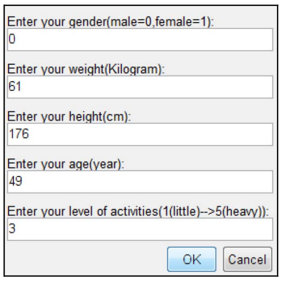

Figure 7. Screenshot of the personal data as input of the NCS.

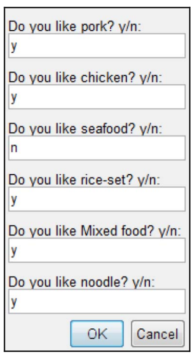

Figure 8. Screenshot of user 1's dietary preferences.

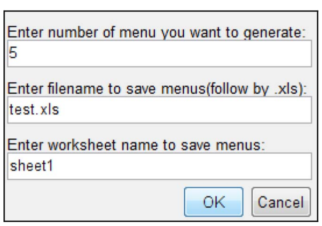

Figure 9. Screenshot of user 1's preferences to generate five menus and name the generated food menu suggestions file as " test.xls", with worksheet names under "user 1".

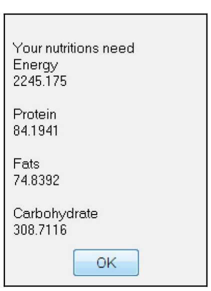

Figure 10. Screen shot of the daily total nutrition requirements for user 1.

V. DISCUSSION & LIMITATIONS

a) Discussion

Eight users are asked to participate. Our proposed method generated an arbitrary five menus for each user. In fact, the NCS can generate "n" number of menus as illustrated above. Table VIII shows the comparison between the actual value and the nutritional requirements of user 1. According to the Harris-Benedict equation, user 1 requires 2245.20 kcal/day. This comprising of 84.20 g. of protein, 74.84 g. of fat and 308.71 g. of carbohydrates. Each row in table VIII shows the actual nutrient value of the five menus generated by our proposed NCS and the percentage resemblance to the user's nutritional requirements (Accuracy row). The last row shows the average percentage resemblance of the caloric content (Energy) of the five suggested menus as well as its component nutrients. It is observed that for the mean percentage resemblance for protein, fats and carbohydrates are lower than that for total energy content (Average Accuracy row). There are probably two reasons for this, 1) it is noted that in Table VII there are "0" values in some of the protein, fats and carbohydrates columns mainly from foodstuffs belonging to either "Drink" group or "Dessert" group. 2) The NCS was designed to mainly perform a food suggestion function to cater for individual total daily energy requirements as described in Fig. 6. It was not designed to match daily essential nutrient (proteins, fats and carbohydrates) compositions as well. This is why the proposed menus compositions of protein, fats and carbohydrates in Table VIII have lower mean percentage resemblance to nutritional recommendations than that of daily energy content.

TABLE VII.
TWO OUT OF FIVE SUGGESTED FOOD MENUS THAT USER 1 MAY CHOOSE TO CONSUME AND THEIR RESPECTIVE NUTRITION COMPOSITION

Menu 1	Food name	Amount	Unit	Unit (Grams)	Size	Energy (Kcal)	Protein (Grams)	Fat (Grams)	Carbohydrates (Grams.)
Breakfast	Soymilk original classic (lactasoy) + Chicken pot pie, frozen entrée (82 g.)	1	MI	300		442.86	13.92	21.99	48.13
Morning snack	Bun steamed, blackbean filled	1	MI	78	6.5 x 3.8 cm.	213.09	5.69	0.30	46.94
Lunch	Rice with shrimp paste (Khao kluk kapi (Thai))	1	MI	283		597.13	26.6	24.9	66.79
	Tipco Plum and Grape Mix Juice 100 %	1	MI	200		70.00	0	0.50	16.00
	Wax jambu, java apple	0.25	KG	223		35.68	0.67	0	8.48
Afternoon snack	Pizza, ham and pineapple (Pizza Hut)	1	MI	103	11 x 11 x 2 cm.	239.47	13.39	8.75	26.78
Dinner	ข้าวเจ้ากล้อง, นึ่ง (2 ทัพพี) + ผัดเผ็ดเครื่องในไก่ใส่มะเขือเปราะ (No English name)	200	GR	200		423.15	17.20	16.70	50.27
	Soybean milk, vegetarian formula no sugar	1	MI	250		157.50	7.00	8.00	15.00
	Toddy palm, cotyledon	1	MI	39	6 x 5.5 cm.	45.24	10.26	0.04	0.94
	Total Nutrition					**2224.13**	**95.50**	**81.19**	**279.33**

Menu 2	Food name	Amount	Unit	Unit (Grams)	Size	Energy (Kcal)	Protein (Grams)	Fat (Grams)	Carbohydrates (Grams.)
Breakfast	Soy milk plus (vitamilk) + Croissants, butter (size 5.9 x 14 x 3.7 cm.)	1	MI	200		403.60	9.92	19.60	47.48
Morning snack	Jellies, all kinds	1	MI	90		239.40	0.13	0.02	62.95
Lunch	Fried rice noodles, Thai style	1	MI	286		677.82	22.02	35.17	68.06
	Pineapple juice, canned	1	CU	200		100.00	0.20	0	25.40
	Rose apple, green	3	LA	192	7.5 x 5 cm.	59.52	0.96	0.18	14.01
Afternoon snack	Fish based snack with seasoning	1	GR	50		167.00	12.25	0.95	27.35
Dinner	Rice, polished, steamed (1.5 CU) + Ground pork with tomatoes and chilli paste, Northern style (Nam Prik Oong (Thai))	0.5	CU	100		407.32	26.79	18.13	34.69
	Unif Mix Fruit Juice with Green vegetable Juice 100%	1	MI	200		100.00	0	0	25.00
	Mango, pimsen-mun variety, ripe	1	MI	204	12 x 8 cm.	130.56	29.78	0.40	2.04
	Total Nutrition					**2285.22**	**102.06**	**74.47**	**307.00**

In Table IX, notice that all the user's menus have higher percentage resemblance values in terms of energy content than for their nutrient composition. In particular for user 2, we have evaluated that the NCS might have matched the wrong foodstuffs due to his career as a badminton athlete. Due to his occupational demands, he trains for over 8 hours a day, he requires some specific high caloric food items to meet his daily energy expenditure. He needs almost double the amount of energy that is usually required. This is as follows: energy = 3057.86 Kcal. (protein = 114.67 grams, fats = 101.93 grams, carbohydrates = 420.46 grams). This translates to a breakfast energy requirement of 1070.25 Kcal (protein = 40.13 grams, fats = 35.67 grams, carbohydrates = 147.16 grams). As the result, within the database there are no foodstuffs that possess such high-energy content. The NCS therefore could only suggest the breakfast menu with an energy content of 503.6 Kcal. Based on the NCS algorithm if the breakfast menu nutrition composed of less than 35% of daily energy intake, as in user 2, the NCS would suggest him to consume more morning snacks. In user 2's case, in order to resolve this energy demand-recommendation discrepancy the NCS had to additionally suggest snacks amounting to 252.06 Kcal. The final proposed breakfast intake subsequently totaled to 755.66 Kcal, which was still 314.59 Kcal short of his calculated nutritional requirements. That is why the mean percentage resemblance (Accuracy) from the five menus of user 2 is lower compared to the others.

TABLE VIII. COMPARISONS BETWEEN ACTUAL NUTRITIONAL VALUES AND NUTRITIONAL REQUIREMENTS FOR USER 1

User 1	Nutritional requirements			
	Energy (2245.2 Kcal)	*Protein* (84.2 g)	*Fat* (74.84 g)	*Carbohydrates* (308.71 g)
Actual value from menu 1	2224.13	95.50	81.19	279.33
Accuracy	99.06 %	86.60 %	91.52 %	90.48 %
Actual value from menu 2	2285.22	102.07	74.47	307.00
Accuracy	98.22 %	78.78 %	99.5 %	99.45 %
Actual value from menu 3	2253.01	102.97	68.61	306.50
Accuracy	99.65 %	77.71%	91.68 %	99.28 %
Actual value from menu 4	2283.79	100.62	67.85	318.23
Accuracy	98.28 %	80.50 %	90.66 %	96.92 %
Actual value from menu 5	2353.40	93.40	68.31	346.70
Accuracy	95.18 %	89.07 %	91.27%	87.70 %
Average Accuracy	**98.08 %**	**82.53 %**	**92.93 %**	**94.77**

b) Limitations

Although this NCS has several advantages over previous designs it can only provide counseling for teenage to adult users without chronic disease. Due to its limited food database it is also unable to sufficiently propose food menus catered for persons with extremely high daily energy expenditures, for example, professional athletes.

TABLE IX. ACTUAL ACCURACY PERCENTAGE AVERAGE COMBINING FIVE MENUS OF EACH OTHER

Nutrition parameters	Energy (Kcal)	Protein (grams)	Fat (grams)	Carbohydrates (grams)
User 1	98.08 %	82.53 %	92.93 %	94.77 %
User 2	91.21 %	74.31 %	94.69 %	87.28 %
User 3	94.73 %	83.20 %	93.20 %	89.78 %
User 4	98.94 %	90.78 %	92.62 %	97.33 %
User 5	98.56 %	94.34 %	94.73 %	94.01 %
User 6	96.25 %	82.75 %	94.26 %	95.48%
User 7	96.75 %	86.51%	95.11%	95.34%
User 8	97.01%	83.12 %	92.69%	91.33%

VI. CONCLUSION AND FUTURE WORK

The results from the eight user volunteers suggest that the NCS is capable of generating individual menus for three meals (breakfast/lunch/dinner) and also offering a variety of foodstuff choices. Overall the users were satisfied with the program and its interface with many willing to consider using it again. The NCS can be useful for people who are concerned with their health and more specifically, their dietary habits.

This paper has described the design and implementation of the NCS that combines two technologies, K-means clustering and expert system, in order to assist people in suggesting a customized food menu that caters to their nutritional requirements.

The NCS can be extended to more users by adapting it for use on mobile phones (SMS or Internet based via a phone application). And this could be enhanced by adding more foodstuffs in the database in order to give a counseling to all sort of users such as sportman, children, patients, the elderly that vary greatly in nutrition. Future work has to be done for comparing whole of nutrition between actual nutrient value and nutritional needs to counseled daily intakes menus.

To compare the NCS with nutritionist, Table X is the average nutrient value of two menus from nutritionist for user 1. The result is 2080.95 Kcal. of energy, 79.77 g. of protein, 92.18 g. of fats, and 234.25 g. of carbohydrates. Like table X, the average nutrient value from the NCS that is 2245.68 Kcal. of energy, 98.78 g. of protein, 77.83 g. of fats, and 293.17 g. of carbohydrates as shown in table XI, the average accuracy of the NCS with respect to the nutritionist is shown in table XII, containing 91.65% of energy, 76.20% of protein, 84.43% fats, and 74.85% of carbohydrates. This means that the NCS might be helpful to nutritionist to create new various food menus with high accuracy.

TABLE X. THE AVERAGE NUTRIENT VALUE OF TWO FOOD MENUS FROM NUTRITIONIST'S RECOMMENDATION

Nutritionist's Recommendation				
Menu No.	Energy (Kcal)	Protein (Grams)	Fats (Grams)	Carbohydrates (Grams)
1	2005.12	86.10	70.08	258.38
2	2156.77	73.44	114.28	210.11
Average	**2080.95**	**79.77**	**92.18**	**234.25**

TABLE XI. The Average Nutrient Value of Two Food Menus from the NCS

NCS				
Menu No.	Energy (Kcal)	Protein (Grams)	Fats (Grams)	Carbohydrates (Grams)
1	2224.13	95.50	81.19	279.33
2	2285.22	102.06	74.47	307.00
Average	**2254.68**	**98.78**	**77.83**	**293.17**

TABLE XII. The Average accuracy between Nutritionist's Recommendation and NCS

Energy (Kcal)	Protein (Grams)	Fats (Grams)	Carbohydrates (Grams)
91.65%	76.20%	84.43%	74.85%

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