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A RECOMMENDER SYSTEM SUPPORTING DIET PLANNING IN HOSPITALS (RES-DIP)

Chakkrit Snae Namahoot[1,2,*], Michael Brückner[3]
and Chayan Nuntawong[4]

[1]Faculty of Science
[2]Center of Excellence in Nonlinear Analysis and Optimization, Faculty of Science
[3]Naresuan University International College
Naresuan University
Phitsanulok 65000, Thailand
[*]Corresponding author: chakkrits@nu.ac.th; michaelb@nu.ac.th

[4]Faculty of Science and Technology
Nakhon Sawan Rajabhat University
Nakhon Sawan 60000, Thailand
chayan@nsru.ac.th

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Abstract. *We show the results of a system prototype for clinical diet planning support. The system analyzes photos of patients' plates before and after meals. The data analysis process uses the Leftovers Evaluation Management (LEM) based on a Convolutional Neural Network (CNN), which assesses the amount of food left on the plate (or the level of consumption) as a percentage and classifies each food item based on the meal plan. The consumption of food items is evaluated in steps of 1/4, 1/2, 3/4, and 1, which improves system performance. The results of the consumption analysis are used to guide diet planning in a flexible way. The ingredient selection process takes the data analysis from LEM using an acceptable low amount of leftovers (e.g., < 50%) and compares ingredients with high nutritional values. This process is used to recommend the best ingredients and meals derived from the ingredient selection based on a low amount of leftovers and high nutritional values of food items to be added to the menu plan. A rule-based component applies a food ontology with nutritional data and the local recipe database. This paper details the process design together with appropriate user interfaces to create a collaborative work environment for the clinical staff, dietitians, and the procurement department. The results show that with a dataset of 126 annotated food items on 504 images the proposed system yields an overall accuracy of 88.61% for leftover analysis and 81.50% for food item classification.*

Keywords: Food leftovers analysis, CNN, Planning and optimization process, Decision support system

1. **Background and Previous Work.** Diet planning for personal use is usually an easy task when appropriate foods are available and affordable. Diet planning for the many patients in a hospital can be a complex and challenging task [1]. Clinical diets aim at treating and preventing suffering from malnutrition. For this study, malnutrition is seen as deficient or imbalanced nutrition regarding energy, proteins, and other nutrients, which leads to adverse effects in the human body condition [2].

In this paper, we use the following terms: *Diet* is the sum of food that a patient consumes over the period of stay in the hospital, *Food* consists of the substances consumed to support the functions of the patient's organism, *Nutrition* is the sum of all substances provided by food to support the patient's organism in a balanced way, *Malnutrition* is characterized by either under-nutrition or over-nutrition, and *Meal* in a hospital is usually

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served to a patient on a tray and comprises appetizer, main course, and dessert. The sum of all meals is the diet, and the sum of all diets is the menu. In this paper, we consider only regular diets.

The diet plan supports the provision of food in a regulated and supervised process to maintain body functions and prevent or treat diseases. Of course, clinical diet plans need to be aligned to regional food consumption habits and seasonal availability to obtain high patient satisfaction [3,4].

Traditionally, the diet plan is the result of a tedious process that is based on the standardized recipe database including such constraints as seasonal availability, budget, and nutritional value [5]. In the recent decade, tools have been developed to support the planning process: Semantic Web tools and other analytic components [6].

1) The task of automatic recognition of food on arbitrary images is a hard one. This is because food products usually do not show shapes and textures that are distinctive enough to be easily analyzed based on images. In addition, current methods work best with certain spatial arrangements, which place the structures in upright positions or separate sections of a plate. For this reason, the image analysis of well-defined separate plates, which are used in the gastronomy of hospitals and other institutions, is possible with simpler methods.

Besides other tools, food imaging has made considerable progress in recent years, stimulated by the introduction of Convolutional Neural Network (CNN), which has led to far more reliable food recognition [7]. Kagaya et al. applied a deep learning approach together with State Vector Machine (SVM) processing to analyzing a wide range of types of food images [8]. They found that color parameters are important for detecting types of foods on images of arbitrary menus or food items. Since they used image sets of food logging apps, the image analysis had to deal with a wide variety of local meals worldwide, the top six food items mostly annotated in the food logging were Rice, Miso soup, Green salad, Natto, Yogurt, and Cold tofu, which are not among the most popular ingredients in Thai diet planning, besides rice. With this limited number of food items, they evaluated the performance of the CNN approach compared to the baseline method.

In [9] a system is proposed using pre-segmented meal images, which they exhibited to a 6-layer deep CNN for food classification. The segmentation allowed the generation of sufficient training samples. They also used an annotated dataset of food items. We adapted this approach to our problem since the pictorial information yields to pre-segmented images of meals (see the photo of the plate used in hospital within Figure 1).

2) Food ontologies cover a variety of informational areas and help gather data from various sources on the Internet. The vocabulary, organized in a hierarchy, together with logical relationships builds an ontology for system integration and automatic data manipulation [10]. In the following, a brief overview of existing food ontologies is provided.

FoodOn, an open-source ontology resource being created by a consortium of labs and information specialists, serves as an unambiguous controlled vocabulary for all aspects of food: global food traceability, quality control, and data integration [11]. FoodOn conceptualizes animal and plant food sources, food categories and products, food processing, and food preservation/packaging. However, at the time of the development of RES-DIP (early 2020), FoodOn lacked concepts about culinary dishes and appropriate combinations of food products, which is needed for creating menu plans. The main obstacle for using the ontologies mentioned is the language used for describing food items and classes. Almost all food ontologies lack concepts described in Thai language, which is the main language of the data source used for analyzing nutrients available from the meals [12].

Therefore, we extended FOODS, a food ontology previously developed by the authors [13] and included concepts for managing complete three-course menus as typical for Thai hospital catering. A description is provided in the next section.

The recommender system prototype presented here is a result of collaborative design and development by dietitians, nutritionists, and information specialists to obtain a flexible and usable tool, which streamlines the process of dietary planning in hospitals. The medical experts acted as the critical test persons to provide input for improving the user interface and process integration.

This paper is organized as follows. Section 2 provides the description of the recommender system and the underlying process, followed by the test results and discussion in Section 3. Conclusions are drawn in Section 4.

2. **System and Process Description.** A Recommender System supporting Diet Planning in hospitals (RES-DIP) typically involves five different roles, just as the traditional planning process: a senior dietitian, a doctor (or senior nurse), a member of catering staff, allied health professional, and a patient representative. In this paper, we are concerned only with the dietitian. The recipients of the planning result are the procurement and the finance departments, represented here by "purchasing".

We assume that the data used for the planning process are available as a standardized recipe database, which includes detailed nutritional data (see, for example in [12]). This ensures that the menu can be checked effectively, and malnutrition can be prevented. The introduction of new meals with their standardized recipes is a step-by-step process, and we assume that this has been performed before using the part of the diet planning process presented here.

As can be seen in Figure 1, the process uses data from the Patient Information System (PIS) to fetch name, patient ID, and other personal data; moreover, room number, and bed number are used to monitor personal diets during the stay in hospital.

Before each mealtime, a photo of the plate is taken in the catering unit to document the initial amount of food served to patients. This photo is stored in the Photo Database (PB) and acts as the basis for comparison of the patients' consumption level after the

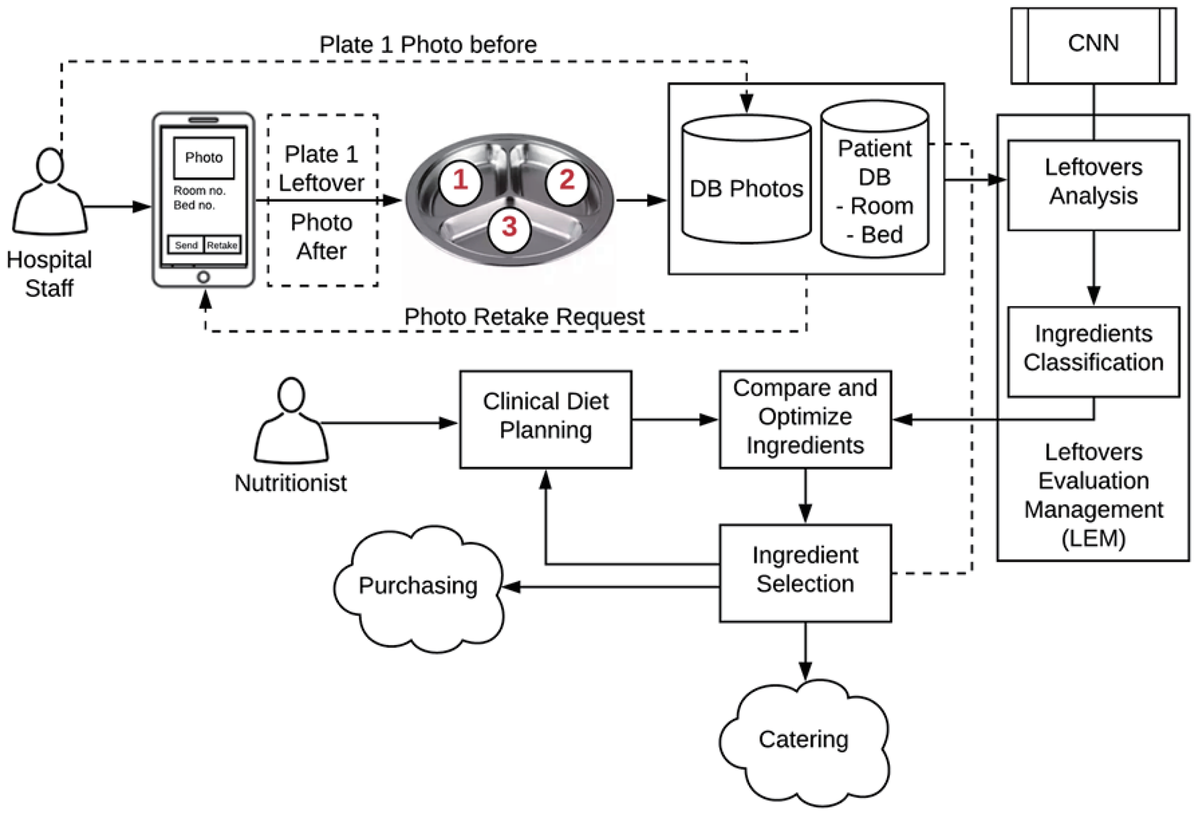


FIGURE 1. Process architecture of RES-DIP

meal. The individual meal is served on a tray with a barcode, which links the photo to the meal ID, the room number, and the bed number. After the patient has finished the meal, the nurse takes a photo of the tray including the barcode. The photo is sent to the PB. Then, the comparison component analyzes the amount of food left as a percentage. The food consumption is the complement to this amount and is stored in the PB. In case, the photo is missing in the PB (or cannot be processed because of other reasons) for the current mealtime, the system notifies the nurse for retaking the photo.

The successful comparison of the photos before and after triggers the leftovers evaluation. This comparison is called Leftovers Evaluation Management (LEM) and is based on a Convolutional Neural Network (CNN) that generates the amount of food left on the plate in steps of 1/4, 1/2, 3/4 and 1 to speed up this step in the evaluation process. For the consumption analysis of leftovers, we use Formulae (1) and (2) to calculate percentages.

In this research, we applied the CNN from [9] in feature extraction to classifying the details of each food item in the plate. A four-layer CNN was used for meal recognition.

A dataset of 126 images of different meals was created using data augmentation. The images contain in total 504 food items and were downscaled and cropped to 32×32 pixels image of each food type (ignores background pixels) before fed to the CNN. Our approach comprises four main steps: data augmentation, meal training, meal recognition, and LEM.

1) Data augmentation: using label preserving transformations since our data set is small. Thus, this technique can increase the amount of data by adding slightly modified copies of already existing data such as flip, rotation, crop and translation. This can help reduce overfitting when training meals with CNN, also training loss is steadily declining, along with validation loss and the accuracy keeps improving (as can be seen in Table 1).

Table 1. Accuracy of meal training: CNN with learning rate at 0.001 and activation function ReLU

Epoc	Train_loss	Valid_loss	Accuracy	Time
0	0.287476	0.212928	0.789000	01:26
1	0.298068	0.447177	0.736000	01:25
2	0.255472	0.341295	0.776000	01:24
3	0.147140	0.299619	0.783000	01:25
4	0.089102	0.286042	0.793000	01:25
5	0.058010	0.224929	0.812000	01:24
6	0.054570	0.257698	0.811000	01:25
7	0.053260	0.218586	0.815000	01:24

2) Meal training: using the created patch dataset we train a CNN with a four-layer architecture. The network has four convolutional layers with 5×5 kernels; the first three layers have 32 kernels while the last has 64, producing equal number of feature maps. The ReLU (Rectified Linear Unit) is used for the activation function.

3) Meal recognition: meal items classification is based on a 5-fold cross-validation technique. Each meal item is classified and reported to the CNN output, then sent to LEM for analysis.

4) LEM: is the component used for evaluating leftover from patients and for planning for suitable ingredients.

The leftovers of the meal are evaluated by using Formula (1):

$$\frac{\sum_{i=1}^{n} Ing(i) \times 100}{n} \tag{1}$$

where Ing is the leftover of each ingredient in the meal and n is the number of main ingredients found in the meal. Main ingredients are all ingredients except condiments (spices, herbs, sauces).

For example, after the ingredient leftovers (four main ingredients, i.e., rice, egg, pork and tofu, $n = 4$) are analyzed and result in the percentage of each ingredient ($Ing(1)$ is rice = 25%, $Ing(2)$ is egg = 0%, $Ing(3)$ is pork = 25% and $Ing(4)$ is tofu = 75%), the sum of all ingredient leftovers is 125%, then divided by 4 (the number of ingredients), which equals 31.25%. This means that the leftovers percentage of this meal is 31.25%. Similarly, the evaluation of ingredient leftovers is calculated with Formula (2):

$$\frac{\sum_{j=1}^{m} Ing(i,j) \times 100}{m} \tag{2}$$

where $Ing(i,j)$ is the leftover of each ingredient i in the meal j and m is the number of the served meals.

For example, after the ingredient leftovers (four main ingredients (i), i.e., rice ($i = 1$), egg ($i = 2$), pork ($i = 3$) and tofu ($i = 4$)) are analyzed and result in percentage of ingredient 1 meal 1 ($Ing(1,1)$) to ingredient 1 meal 6 $Ing(1,6)$ are 25%, 25%, 25%, 50%, 25%, and 0%, respectively, and the sum of rice leftover is 150%, which when divided by 6 (number of served meals) is equal to 25%. This means that the leftover of rice is 25% on average for all meals served. The ingredient selection process takes the data from LEM and supports the decision making by ranking food items by percentage. Then, the system uses the rule base to recommend best ingredients and meals derived from the ingredient selection to be added to the menu plan by the following sub-process.

1) Check and return all ingredient leftovers with a percentage less than 50%.
2) Extract all ingredients with high nutritional value from the ingredient selection system which are ranked and selected in recommended position.
3) If ingredients have the low percentage of leftovers and have high nutritional value, take all ingredients, and rank them in order.
4) Select ingredients from Step 3) and recommend meals derived from these ingredients in accordance with the recipe database.
5) Consider other preparation methods for ingredients with leftover percentage $> 50\%$ and high nutritional value.
6) Go to Step 3) until ingredients selection and recommended meals are covered and complete plan for the next 14 days, then go to Step 1).

The dietitians can use the result with the identified ingredients and recommended meals for the menu planning in the following weeks, and they can check available recipes and meals with the selected ingredients or apply adjustment where it is appropriate.

The original FOODS ontology [13] was later adapted for being used for the In-Patient Diet planning system called DIPS [6]. This version has been further improved with the Material class (Ingredients), Nutrient classes, Disease classes, RegionalCuisine, Dishes, and PreparationMethods. Regarding the Seasons class, ontology design concepts were adapted to recommend ingredients suitable for the current season. In addition, we have designed a new class of food and nutrition for patients, including the menu class, meal class (Meals), Religion class, patient class (Patients), Gender class, and Types of Diets to provide a comprehensive introduction to the diet for the patient, race, religion, among others.

The extension of the FOODS ontology includes not only new classes supporting hospital menu practices but also some new relations used for reasoning. The extended FOODS ontology uses the

- "has_quality" relation to cater for chemical and physical components and properties of a food product that are not discernable,

- "has_main_ingredient" when the ingredient is the primary component of the food product described,
- "goes_along_with" when the food product is a conventional choice for a meal, e.g., salmon steak with lemon.

The extensions to FOODS support the planning process by identifying the main proportions of an ingredient ("has_main_ingredient"), such as strawberry yogurt, the main ingredient of which is the dairy product. Other relations included foster menu planning by allowing or discarding products to be planned as part of a specific dish (as in the relation "goes_along_with").

3. **Results and Discussion.** Staff need to install the RES-DIP app on their smartphones to communicate with the LEM of RES-DIP. When taking photos of the plates after patients have finished their meals, staff must follow the RES-DIP/LEM Protocol, which is usually finished in less than seven steps.

1) Open the RES-DIP app on the phone and use best resolution with flash
2) Place the plate on a plane surface
3) Remove anything that does not belong to the food, e.g., tissue or cutlery
4) Take the picture plate by plate from the top
5) Make sure the plate fills the screen and the barcode is visible
6) After you have taken the picture, check the positive response of LEM and continue with the next plate (Step 2))
7) If the response is negative, continue with Step 4) one more time

The total accuracy of the food item classification is 81.5%. The training loss is steadily declining, along with validation loss and the accuracy is increasing without overfit. The accuracy seemed not too high due to the fact that some food item images are not clear enough when taking photos from meal menu.

Figure 2 shows the user interface regarding the nurse's photo taking in the patients' rooms. The photo shows that the patient has not eaten anything, so the leftover analysis will be at 100% for all ingredients. The picture does not show the card placed on the tray identifying room and bed number. After taking the photo the nurse will see the room number and the bed number below the photo to ensure that the data correspond with the patient.

After the photo has been taken, the nurse or staff clicks the "Send" button, and the system responds quickly to confirm that the photo is ready for leftovers analysis (with check marks showing) and other information, such as the date and time, bed no. and room no. If red cross check marks appear on the mobile screen, the staff must click "Retake" to take the photo again to ensure a photo quality that can be analyzed.

Figure 3 and Figure 4 show the results of LEM following the analysis of the photos. This analysis includes the comparison of the amount of food before and after the meal. Moreover, the photos received through the PB interface are automatically correlated to breakfast (BF), lunch (L), and dinner (D) using time stamps. Figure 3 shows results for breakfast (BF) served with steamed rice and stewed eggs with pork. The system classifies ingredients from the meal into four main food items: rice, egg, pork, and tofu. The level of consumption for this meal is quite high (with 25% average leftovers), which indicates patients' good response to this meal, especially for egg and pork (leftovers 4.17% and 12.5%, respectively). However, the tofu seems to lead to higher leftovers with 58.33%. As a result, the system will, in accordance with the recipe database, either not recommend tofu as a food item for meals in the coming weeks, or switch to other types of food preparation, such as fried tofu, or use other types of tofu for cooking, e.g., fresh tofu normally used for vegetable soup.

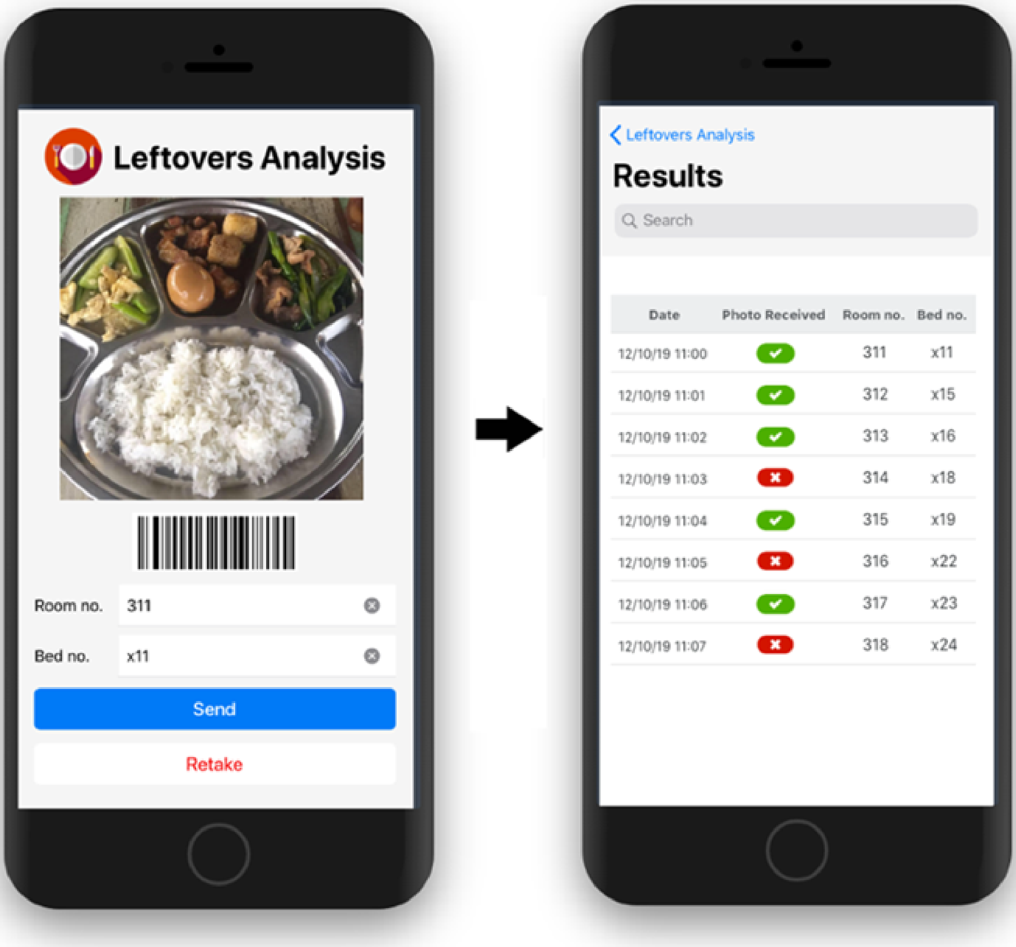


FIGURE 2. User interface for hospital staff (nurse)

Figure 4 shows the lunch meal with noodles, pork in gravy sauce, and kale. The system classifies the main ingredients of the meal into three food items: noodle, kale, and pork. The percentage of average leftovers from this meal is 41.66%, which indicates that patients had problems with its consumption, especially with the noodle and kale (45.83% and 45.83%, respectively). The pork was consumed at a higher rate with only 33.33% leftovers, but there is still the need to improve its consumption, e.g., by using other types of preparation (grilled pork, fried pork, pork curry, dried red pork, or pork salad). The system proposes such measures if the level of consumption is too low and other preparation methods are available from the recipe database. The selection of appropriate preparation methods is performed in a similar way as has been reported in a previous paper [14].

Figure 5 presents the results of the menu optimization within RES-DIP. The optimization takes all results obtained by LEM (Figure 3 and Figure 4) and summarizes them on a day-by-day basis to identify main ingredients with high consumption (= low leftover rate) and high nutritional values adapted from a previously developed system [12]. The resulting data show the best meal of the day as well as recommended meals derived from the ingredient selection to be added to the menu plan for the next weeks. The result shows that the best ingredients ranking in terms of the lowest leftovers are shrimp, cauliflower, egg, pork, and rice, since their leftovers are less than 25%. Thus, all these ingredients are selected for the menu planning in the following weeks, and the recommended meals using the selected ingredients are stir-fried cauliflower with shrimp, minced pork omelets, steamed rice and egg, and fried rice with shrimp and/or pork. On the other hand, the three ingredients noodle, kale, and tofu are not selected, even though they have high

Leftovers Analysis System

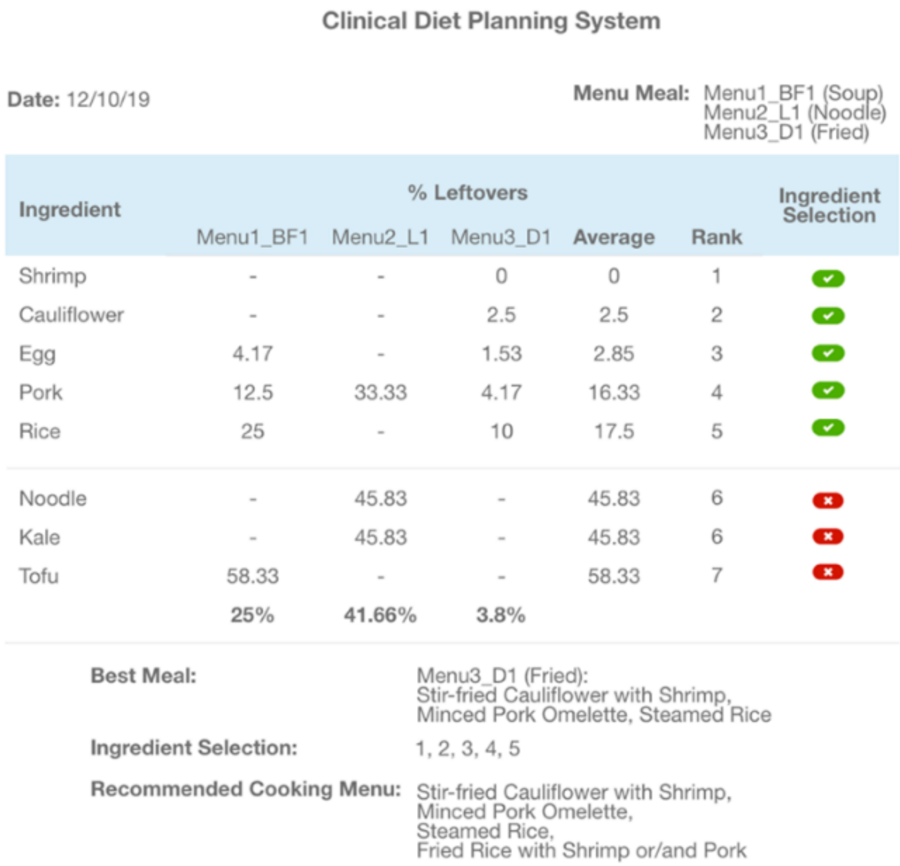
Room/Bed	Meal Time	Meal	Leftovers Rice	Egg	Pork	Tofu	Total per Meal
311/x11	BF	Rice+Stewed Eggs with Pork	25%	0%	25%	75%	31.25%
312/x15	BF	Rice+Stewed Eggs with Pork	25%	0%	0%	50%	18.75%
313/x16	BF	Rice+Stewed Eggs with Pork	25%	0%	25%	75%	31.25%
314/x18	BF	Rice+Stewed Eggs with Pork	50%	0%	0%	100%	37.5%
315/x19	BF	Rice+Stewed Eggs with Pork	25%	25%	25%	25%	25%
316/x22	BF	Rice+Stewed Eggs with Pork	0%	0%	0%	25%	6.25%
...	...	...	...	...	...	...	...
		% Ingredient Ingredient Classification	**25%**	**4.17%**	**12.5%**	**58.33%**	**25%**

Figure 3. Consumption analysis results shown as percentage of leftovers (breakfast)

Leftovers Analysis System

Room/Bed	Meal Time	Meal	Leftovers Noodle	Kale	Pork	Total per Meal
311/x11	Lunch	Noodle with Pork in Gravy Sauce and Kale	25%	50%	25%	33.33%
312/x15	Lunch	Noodle with Pork in Gravy Sauce and Kale	75%	50%	0%	41.67%
313/x16	Lunch	Noodle with Pork in Gravy Sauce and Kale	25%	50%	25%	33.33%
314/x18	Lunch	Noodle with Pork in Gravy Sauce and Kale	50%	100%	50%	66.67%
315/x19	Lunch	Noodle with Pork in Gravy Sauce and Kale	25%	25%	25%	25%
316/x22	Lunch	Noodle with Pork in Gravy Sauce and Kale	75%	0%	75%	50%
...	...	...	...	...	...	...
		% Ingredient Ingredient Classification	**45.83%**	**45.83%**	**33.33%**	**41.66%**

Figure 4. Consumption analysis results shown as percentage of leftovers (lunch)



Clinical Diet Planning System

Date: 12/10/19

Menu Meal: Menu1_BF1 (Soup) Menu2_L1 (Noodle) Menu3_D1 (Fried)

Ingredient	% Leftovers					Ingredient Selection
	Menu1_BF1	Menu2_L1	Menu3_D1	Average	Rank	
Shrimp	-	-	0	0	1	✓
Cauliflower	-	-	2.5	2.5	2	✓
Egg	4.17	-	1.53	2.85	3	✓
Pork	12.5	33.33	4.17	16.33	4	✓
Rice	25	-	10	17.5	5	✓
Noodle	-	45.83	-	45.83	6	✗
Kale	-	45.83	-	45.83	6	✗
Tofu	58.33	-	-	58.33	7	✗
	25%	**41.66%**	**3.8%**			

Best Meal: Menu3_D1 (Fried): Stir-fried Cauliflower with Shrimp, Minced Pork Omelette, Steamed Rice

Ingredient Selection: 1, 2, 3, 4, 5

Recommended Cooking Menu: Stir-fried Cauliflower with Shrimp, Minced Pork Omelette, Steamed Rice, Fried Rice with Shrimp or/and Pork

Figure 5. Results of meal optimization for dietitian

nutritional value. These ingredients will not be selected during the next planning cycle because they exhibited the highest leftovers (45.83%, 45.83% and 58.33% respectively). However, these ingredients may be selected as appropriate ingredients in the future again if other ingredients show high percentages of leftovers.

For testing, the leftovers were measured using samples of main meals with four different amounts of leftovers (Test1, Test2, Test3, and Test4), including meals like 1) noodle with pork in gravy sauce and kale, 2) steamed rice and stewed eggs with pork, 3) stir-fried cauliflower with shrimp, and 4) minced pork omelet. We provide data comparing LEM results with human experts as percentages of leftovers and respective averages. On one day staff nurses checked the leftovers on each single plate for the three meals of the day consisting of three dishes (starter, main and dessert) and noted their evaluation on sheets provided by researchers. Dietitians calculated the average values, which were then compared with the results gained by LEM. The accuracy measure is the overall average from the experts (43.22%) divided by the LEM average (48.78%), i.e., 88.61%.

The results of the system test show that the difference between expert assessment and the system results are high when there are a lot of leftovers, especially in cases like Meal1, which consists of a higher number of food items to assess. Thus, it is difficult for the system to identify and calculate the leftovers of each ingredient. Besides that, the gradation is rough with only four steps of 25%, 50%, 75%, and 100%. As an example, in Test2/Meal1 the system assessed leftovers for noodles, kale and pork 25%, 50% and 25%, respectively, which leads to the average of 33% measured by system. The experts assessed leftovers of the same plate as follows: 12% of noodle, 20% of kale and 8% of pork resulting in an average of 13%. For smaller amounts of leftovers, the differences between expert and system assessments get smaller, though.

4. **Conclusions.** This paper has detailed an improved process of computer-assisted clinical diet planning employing picture-based analysis of actual food consumption, or leftovers, by patients. The leftover analysis process has used pictures of actual plates analyzed with a CNN for the amount of foods consumed. The system then has consulted a food database and the authors' extended version of a previously developed food ontology, FOODS. The resulting data have been employed to plan the complete menu for the coming two weeks. This plan has then been presented to dietitians responsible for the clinical menu plan for approval.

A limitation of this research is the focus on regular diets. Future developments should include modified diets that are appropriate for diverse groups of patients, e.g., patients with diabetes and renal deficiencies [15].

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