Addressing Malnutrition in School-Aged Children with a Diet Recommender System

Uduakobong M. Umoren
Department of Computer Science
Federal University of Technology Akure

Bolanle A. Ojokoh
Department of Information Systems
Federal University of Technology Akure

Ijarotimi, O. S.
Department of Food Science & Technology
Federal University of Technology Akure

Abstract:- Automated recommender systems have been developed to make up for human inadequacies in decision making while solving the information overload problem. They have also found profound use in the area of diet and nutrition. Nevertheless, child nutrition in recommender systems is yet under researched, with very few works found in this area. This research work employs a switching hybrid recommendation technique that is a combination of user-based collaborative filtering and human expert knowledge for both healthy and malnourished children; to cater for the nutrition needs of children on a large and much improved scale while being accessible and available to children, parents and care-givers in different locations at the same time. Six elementary schools in Nigeria were visited for data gathering on children food interests, likes and dislikes. Open ended and dichotomous questions were used to obtain vital information for the system; and these responses are incorporated as initial user and food database to check the cold-start problem. Waterlows' classification model was used to profile and classify users into their health classes and user-based collaborative filtering algorithm was used to recommend meals to the users based on user-user similarity. Human expert knowledge built from interaction with nutritionist was incorporated into the system and used in the recommendation process for both healthy and malnourished children. System evaluation results show the overall optimal performance and acceptance of the system. The results of this work can be adopted to reduce the scourge of malnutrition in children through healthy diet provisioning, especially in the Nigerian context.

Keywords:- *Malnutrition; Diet Recommendation; School Aged Children; Allergy; Nutrition.*

I. INTRODUCTION

Malnutrition refers to deficiencies, excesses or imbalances in a person's intake of energy and/or nutrients, and it involves undernutrition, which includes stunting (low height for age), wasting (low weight for height), underweight (low weight for age) and micronutrient deficiencies (vitamins and minerals), and overweight, obesity (Collins et al., 2010; Mandal, 2019). Undernutrition is very common in developing countries, and characterized with body wasting, stunted growth, impaired brain development and academic performances, particularly in children (Brown & Pollitt, 1996; Phalen, 2013; Coleman, 2018; Thomas, 2018). Malnutrition can be suffered by anyone, it is prominent in sub-Saharan Africa and children are more at risk than any other age bracket (UNCEF/WHO/World Bank, 2017). According to UNCEF/WHO/ World Bank (2017), over 52 million children are suffering from wasting while 154.8 million and 40.6 million are stunted and overweight, respectively.

In Nigeria, the prevalence of undernutrition among children is on the increase with statistics showing over 2 million children are suffering from Severe Acute Malnutrition (SAM) with stunting, wasting and undernutrition rates given as 43.6%, 10.8% and 31.5%, respectively (Tyessi, 2018). The ideal way of preventing or managing malnutrition among children is through adequate diet recommendation and provisioning (Streit, 2018); and with technological advancements as we presently have, these recommendations can be automated and provided as systems that can be available and accessed on a large scale.

Recommender systems are designed to deal with the problem of information overload through the filtering of vital information fragments out of large amount of dynamically generated information according to user's preferences, interests or observed behaviours about item (Isinkaye *et al*., 2015). They present the most suitable option to a user out of a vast amount of available options open to a user in any field; and they have also been employed in areas including social networking, movie recommendations, music and entertainment recommendations, food and restaurant recommendation, e-commerce and e-library among others (Sharma & Singh, 2016). Food and diet recommendations for children is an area of interest that is yet to be widely given attention as a research area and is relatively under researched (Trattner & Elsweiler, 2017). Few works have targetted dietary plan for children (Hazman & Idrees, 2015; Kale & Kuti, 2015); and that if malnutrition must be addressed adequately, then there is need for further works in the area of child nutrition that will provide systems to tackle the problem and complement human ability by recommending adequate diet plans to the children in order to promote their nutritional

ISSN No:-2456-2165

and health welbeing (FAO, 2013; UNICEF *et al.*, 2017). A child diet recommender system will give a helping hand to parents/guardians in the provision of healthy meals to the children; keeping the children healthy by recommending personalized meals that will give each child the right amount of food and nutrients needed, preventing malnutrition rather than looking for cure later on.

In this present work, user-based collaborative filtering and human expert knowledge recommendation techniques are incorporated into the development of a diet recommender that promote child health while reducing disease risks hence promoting nutrition as therapy to nurse low weight children to health and from this provide a nutrition plan for meals that can be served at home or school. The target users of this system are school-aged children ranging from ages four to twelve (4 - 12) years.

This work contributes a platform from which malnutrition in children can be reduced through healthy diet provisioning using the combination of user-based collaborative filtering technique and human expert knowledge by providing:

- a nutrition plan that regulates food intake and increases diet quality of meals served to children at home or school;
- remedy through meals for protein energy malnutrition (wasting) and under-nutrition.
- consideration for dislikes and allergies to also recommend substitute meals.

The rest of this paper is organized as follows: section 2 presents related works reviewed and section 3 describes the proposed method for the system in detail while section 4 presents the experimental results and discussion. Finally, conclusion and direction of future research are presented in section 5.

II. REVIEW OF RELATED WORKS

Recommender systems have been around for some time now with several techniques being employed in various food related systems. Literature exists for such systems like fuzzy logic based nutritional recommendations (Priyono & Surendro, 2013), dietary management system using ID3 (Kale & Auti, 2015), interactive recommendations for groups (Elahi et al., 2014), older adults' content-based meal recommender (Ribeiro et al., 2017) and system for those without ability to express choice (De Pessemier et al., 2013). The approaches they stated as used in the works include collaborative filtering (Freyne et al., 2011), content-based (El-Dosuky et al., 2012), various hybrid methods (Harvey et al., 2013; Ojokoh & Babalola, 2015), context-aware methods (De Choudhury et al., 2016), group-based methods (Elahi et al., 2014) and health-aware methods (Elsweiler et al., 2017). Therefore, it is necessary to present in detail works that are related to the recommender system in this work.

In Trattner & Elsweiler (2017), the authors give a comprehensive state-of-the-art in food recommender systems with systems recommending recipes, meal plans, groceries, food items and menus. they give detailed explanations on the algorithms employed, the challenges involved and important future directions. They also identify datasets, nutrition and health resources as resources that could help in food recommender systems; while recommending the capture of important variables through sensors and incorporating such into the models used.

Two ways that the recommendation problem can be reformulated to include nutritional aspects in addition to the user preferences were discussed in Elsweiler et al. (2015); considering the trade-off between user choice and user need. In the work, the first approach selects the best algorithm for estimating top recipes, then calculates calorie levels for the sets of recipes and recommends meals with less fat or calories by minimally reducing the predicted rating. Their second approach calculates nutritional requirements of user based on personal profile using an updated Harris Benedict equation, with daily calorie requirement and compiles recipes that corresponds to the derived nutritional requirements.

A recipe recommendation system built on natural language processing is created in Ueta et al. (2011). their system takes user input which contains a health problem in natural language as text, and a morphological analyzer extracts the noun which is the problem to be handled. The system then matches the noun to a co-occurrence dictionary that contains nutrients which could provide remedy to the condition, recommending dishes in the process. However, from the description of the system it doesn't consider user past search history so user may get same recommendations on every search. Validity of results was not confirmed by a professional dietician. In De Pessemier et al. (2013) the authors combine content-based and collaborative filtering algorithms to create a food recommender system for patients who may be unable to express choice. They obtain patient preferences either by explicit ratings or implicit feedback and they developed a framework in which they store data about preferences, activities, behaviors of patients regarding meals, etc. Explicit prediction of a patient's preference of an item consists of a weighted average of the patient's explicit rating and a prediction of the patient's preference based on implicit feedback for the item; with weighing factor ranging from 0 to 1. Implicit prediction is calculated by means of a weighted average of the implicit feedback for the item, and a prediction based on the ingredients of the item. Finally, personal recommendations for patients are generated using a hybrid recommendation algorithm composed of content-based and collaborative filtering algorithms.

Elahi et al. (2014) extend food recommendation to cover groups using a novel utility function based on matrix factorization algorithm. Their system is said to generate a long-term plan for users in a group with predicted scores from utility function for the entire group being quantified as the aggregation of individual utility scores. Their end product is an Android application with different interfaces for user interaction featuring preference elicitation interface (tag-and-rating-based), group recommendation aggregation and critique based conversational recommendations. Similarly, Ge et al. (2015) used a tag-based matrix factorization recommendation algorithm to design a system that

ISSN No:-2456-2165

incorporates user selected tags to describe food attributes from which food recommendation is offered, motivated by the need for a decision-aid system that can suggest and recommend personalized food options, taking into account user's preferences and eating history. The user rates and tags the recipes and also defines important ingredients they would love; and the algorithm incorporates these to describe food attributes from which food recommendation is offered. However, the developed system cannot be said to be health aware as it recommends foods based on preference and not on the health status of the user.

An automated menu planning system for children was designed in Kale & Auti (2015) in which they used decision tree for classification, to select proper food item that will fulfill nutritional needs of children. They employed ID3 algorithm for decision tree learning to tell which proper food item should be assigned in menu planning in their automated recommendation by dietary management system; with main objective being the construction of the decision tree until the appropriate classification is reached to select the proper food item based on availability such that If food is available and liked by the child, it will be suggested in the menu plan. Expert systems have also been designed to combat the scourge of child malnutrition, such as the one in Hazman & Idrees (2015). Their system considers child growth stage, gender and health status in its attempt to provide users with expert nutrition advice; and comprises the domain layer, inference knowledge and task knowledge. Combining nutrition ontology with the domain models, they feed this into the inference engine. Inference knowledge produces the steps that will be followed in solving nutrition problems and Task knowledge defines system control sequence. However, knowledge validation for proposed system was not carried out and knowledge base was not completed.

To be able to select diet patterns that meet one's needs, Rehman et al. (2017) designed a cloud-based food recommendation system that considers the users' pathological tests results, recommending a list of optimal food items that provide dietary assistance to different people suffering from common diseases. Using the Ant Colony Optimization algorithm to consider users' pathological tests results and from that, recommend a list of food items to provide dietary assistance to users suffering common diseases. Recently in attempting to combat the rise of Diabetes as an epidermic, Padmapritha et al. (2020) developed a system with dual functionality which serves as an artificial pancreas and also provides diet recommendations for diabetes in elderly patients. They use a stochastic framework where the artificial pancreas which they claim can automate insulin infusion, computes the optimal insulin using the model predictive control algorithm; then with carbohydrate values, compute the insulin administration. Using all they available information, they define the diet quality, which serves as a measure to recommend suitable meals for the patients.

Mustafa et al. (2020) in their work developed a knowledge recommender system that serves as an automated sports dietician or nutritionist, which would be readily available to athletes. Knowledge for the system was acquired from dieticians via semi-structured interview which led to the design of the sports nutritionist database. The system calculates calories and macronutrients requirements based on sports category; energy requirement was determined based on basal metabolic rate and physical activity level. Their system has two inference engines: one for meal plan and one for meal reconstruction; and they run with sets of rules through which these match a user profile with a meal plan. They present the design of the system in web and mobile form. However, there was no usability test among target users which would have revealed problems likely to be faced by users; and also, sports nutrition experts didn't evaluate the suitability of meal plans.

More recently in Princy et al. (2021), the authors created a hybrid recommender system with the combination of content-based and collaborative filtering techniques to provide healthy diet recommendations for women. By tracking the eating behaviour of users, food items and ingredients with recipes collected; the system has enough information to give personalized food recommendation. The content-based recommendation part maps food characteristics with user past preferences, eating behaviour and their health problems; and from the result, will persuade user to change behaviour. The collaborative filtering part of the system takes user ratings of a given food item of one user to recommend food items to another user with similar taste and interest. Finally, as regards the focus of this work, Tyessi (2018) in its report from the Multiple Indicator Cluster survey for 2017 had wasting (low weight-for-height) increase from 7.2% (2015) to 10.8% among Nigerian children; showing a 3.6% increase and this makes malnutrition a key contributor to infant mortality, poor cognitive development and increased severity of diseases which in turn adversely affects productivity.

There is a need to provide nutritional care for children in school and at home; which at present needs to be given more attention as children need to have a platform that will provide them with tailored diet plans, keeping them nourished and healthy with increased immunity from diseases. The diet recommender system that this research work presents, contributes a platform from which malnutrition in Nigerian children can be reduced through healthy diet provisioning using user-based collaborative filtering technique while considering user interest, dislikes and allergies. The system presently only covers school-aged children between 4 and 12 years as they need good meals to thrive and grow; and has in its recommendations a vast number of Nigerian dishes.

III. PROPOSED METHOD

Data Collection: Background work of interaction with 507 school pupils from six elementary schools in Akure Metropolis, Nigeria: two (2) private schools and four (4) public schools to learn their food interests, allergies, dislikes, and frequently eaten meals was carried out. This survey was caried out due to the unavailability of data for use in the research work, to overcome the cold start problem. The simple questions were open-ended so the respondents could answer without restrictions while some were dichotomous in

ISSN No:-2456-2165

nature which could be satisfied with a "yes or no" response. The questions were administered in-house since the schools were visited. The choice of sampling technique used here was purposive as children in private schools tend to be more well taken care of as against community primary schools which is seen generally as schools for the underprivileged; and this also helped make the choice of two private schools and four public schools. The questions were answered with the help of the teachers present who guided the pupils with thorough explanation of the questions. The simple interactive questions besides age and gender are given as follows:

Section A:

- What are the types of snacks or meals you usually bring to school for lunch break?
- What are the types of food you don't like if served to you?
- Are there any foods or ingredients that you negatively react to if you eat them? List them.
- Do you follow a meal plan at home? Yes, or No.
- Do you bring food/snacks to school every day? Yes, or No.
- Do you always eat what you bring to school?

While section B got the pupils to fill a meal table they follow or would love to follow.

507 responses were recorded of which 260 (51%) were boys and 247 (49%) were girls. Age distribution was between 6 years and 12 years and the frequency distribution of boys and girls by age is given in table 1.

Pupils Responses Summary			
Age	**Frequency**		**Age Percentage (%)**
	Boys	*Girls*	
12	21	26	9.3
11	59	46	20.7
10	52	63	22.7
9	51	49	19.7
8	47	43	17.6
7	24	16	7.9
6	6	4	2

Table 1:- Pupils Distribution

The responses obtained from these pupils are used as base ratings for the system initial database for ratings and interests, to avoid the problem of cold start which is a challenge for collaborative filtering algorithms. From the responses, a utility matrix was developed in the form of an excel spreadsheet which comprises many of the meals eaten in western Nigeria and also liked by children with their ratings, from which predictions was made for healthy children as shown in Table 2.

S/N	U1	U2	U3	U4	U5	U6	U7	U8
AGE	7	7	9	8	9	9	10	6
GENDER	BOY	GIRL	GIRL	GIRL	GIRL	BOY	GIRL	GIRL
RICE	1	3	2	3	4	5	4	3
BEANS(POTTAGE	1	1	1	2	1	3	4	3
BREAD&TEA	5	3	3	5	3	3	3	4
CORNFLAKES&MILK	1	4	2	2	3	1	2	2
COCOPOPS&MILK	1	1	1	2	2	1	2	1
BREAD&BUTTER	2	3	3	3	3	3	2	2
NOODLES	3	5	4	3	4	3	1	3
YAM&EGG(SAUCE)	3	1	1	3	2	3	1	3
BREAD&STEW(SAUCE)	2	2	3	3	3	3	3	3
OATMEAL	1	3	2	2	3	1	2	2
CASSAVAFLOUR(SEMO)&VEG.SOUP	3	1	1	2	2	2	5	1
RICE&BEANS	3	2	1	3	1	3	4	3
POUNDEDYAM&MELONSOUP	4	1	3	3	3	2	2	3
BEANCAKE(AKARA)&BREAD	2	1	1	2	3	1	2	2
GARRI&MELONSOUP	3	1	2	1	2	3	3	3
WHEATFLOUR&EWEDU	1	1	1	1	2	1	2	2
COCOYAM	1	1	1	1	1	1	1	1
RICE&STEW	2	4	5	3	4	4	5	2
BEANCAKE(AKARA)&PAP	3	1	1	1	3	2	3	3

ISSN No:-2456-2165

PUPURU(CASSAVABASE)&STEW,SOUP	2	2	1	1	2	2	2	2
BEANS&BREAD	2	2	2	3	1	2	3	3
EBA&OKRASOUP	4	3	3	3	2	3	3	3
GOLDENMORN(WHEATMEAL)&MILK	1	4	3	2	3	2	2	2
BISCUIT&TEA	3	1	3	3	1	2	2	1
TUWO(PASTEDRICE)&MELONSOUP	1	1	1	1	1	1	1	1
EBA&VEGETABLESOUP	3	3	2	3	2	4	3	3
RICE&STEW&FISH	3	4	5	3	4	4	5	3
YAMPORRIDGE	4	1	1	2	2	3	3	3
BREAD, FRIED EGG & TEA	4	3	3	5	3	3	3	4
YAM&STEW	3	2	2	3	1	3	3	3
MOIMOI&BREAD	3	1	1	1	3	2	3	1
MOIMOI&GARRI	3	1	1	1	3	3	3	1
MOIMOI&PAP	2	3	2	3	4	3	3	3
AMALA&EWEDU	4	4	2	2	3	2	3	2
SNACKS&DRINK	3	1	2	2	1	2	2	3

Table 2:- Sample Utility Matrix/Dataset

The research work which is based on a switching hybrid system consists of a user-based collaborative filtering algorithm and an expert nutrition-based recommendation part; and the target users of the system are school-aged children of the age range of four to twelve (4 – 12) years.

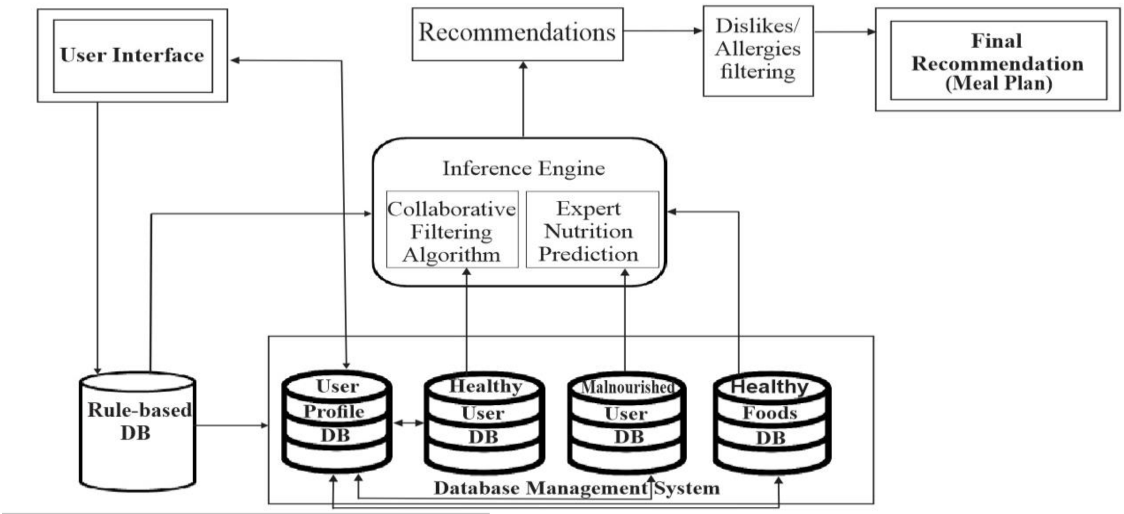

Fig 1:- Architecture of the Diet Recommendation System

The system architecture as shown in figure 1 shows system is developed to provide user-based collaborative diet recommendation for healthy children while providing food recommendations also for malnourished children with the necessary nutrients for their health.

The user supplies information and also obtains recommended plans through the user interface. User age, sex, height, weight and activity level is obtained by the system and used in decision making. The Rule Base stores the set of rules which the system uses to classify users as healthy or malnourished to store them in their respective databases; and the set of rules that determine the number of daily calories for a given user. The database management system stores user profile, healthy user, malnourished user and healthy foods databases; and Inference engine uses the stored rules to make recommendations for a classified user

The meal plan is generated using active user weight-for-height as obtained using Waterlows' classification (Waterlow (1973); Avencena & Cleghorn (2014); Ferreira (2020)) which is an ideal measure for child body weight with respect to height, Activity level (AL), daily needed calories, user interests in meals and ratings given by the user to specific meals, where high ratings construe fondness for meals. Waterlows' classification is obtained as follows:

$$WFH = \frac{Weight\ of\ Active\ User}{Weight\ of\ Normal\ Child\ of\ same\ Height} \times 100 \quad (1)$$

It follows a set of IF-THEN statements (tools) that help in decision making and takes the decision-making ability of a system to a high level of expertise. Potential decisions and outcomes that could occur in a situation are established after which questions are set out regarding specific circumstances or conditions that may or may not be present from which a set of rules are established and written out.

Level of malnutrition is determined by dividing the weight of the child (user) by the weight of a normal child of the same height and then finding the percentage of the outcome. The percentage is then compared to the standard grading which will determine whether child is normal, mildly, moderately or severely malnourished using a set of rules made up of IF-THEN statements. Table 3 shows the different weight-for-height class ranges and their health status while figure 2 shows the system profiling flowchart.

Percentage Weight-for-Height	Health Class
$x \geq 90$	Healthy
$80 < x < 90$	Mild
$70 \leq x \leq 80$	Moderate
< 70	Severe

Table 3:- Health classes

The system takes into consideration the daily required calorie as should be taken by a child. This is arrived at considering child age, gender and activity level (sedentary, moderately active and very active) as shown in table 4.

Gender	Age stage	Activity level/Calories (kcal)		
		Sedentary (calories)	Moderately (calories)	Very Active (calories)
Male	(1–3yrs) Toddler (4-5yrs) Preschool (6-10yrs) Elementary school (11-13yrs) Junior Secondary	1,000 – 1,200 1,200 – 1,400 1,200 – 1,400 1,600 – 2,000	1,000 – 1,400 1,400 – 1,600 1,400 – 1,600 1,800 – 2,200	1,000 – 1,400 1,600 – 2,000 1,600 – 2,000 2,000 – 2,600
Female	(1–3yrs) Toddler (4-5yrs) Preschool (6-10yrs) Elementary school (11-13yrs) Junior Secondary	1,000 1,200 – 1,400 1,200 – 1,400 1,400 – 1,600	1,000 – 1,200 1,400 – 1,600 1,400 – 1,600 1,600 – 2,000	1,000 – 1,400 1,400 – 1,800 1,400 – 1,800 1,800 – 2,200

Table 4:- Activity level/ Daily needed calories
(source: Hazman and Idrees, 2015; Department of Health, 1991)

The calorie portions are set for the course of the day on the ratio of 3:4:3, apportioning more calories to the afternoon meals as more energy is required at this time. Calorie portions can be obtained by

$$cp = \frac{ratio}{total\ ratio} \times daily\ needed\ calories \quad (2)$$

The data management system is made up of the user profile, the healthy user, the malnourished user and the healthy foods/diet databases.

- User profile database: This database houses the variables which the user provides as input on first point of access with the system. On registration (after login details have been accepted and user id generated) the user is required to supply user age, gender, weight, height, food interests, dislikes and allergies. These user inputs are now stored in the user profile database and are used in deciding whether a child is healthy or malnourished; and the level of malnourishment of a child.
- Healthy user database: This is a database of users who meet the conditions set for a healthy child (that is when the percentage WFH is greater or equal to 90%) and which the diet recommendation will be done using a diet database composed in the form of a utility matrix; and comprises of users, their gender and age. The utility matrix comprises many of the meals eaten in western Nigeria from which predictions will be made for healthy children. The meals in the matrix are rated by each user with each meal rated on a scale of one to five; five being the highest and shows how well a person likes a meal and how frequently the meal is taken. It also contains meals disliked by users. This matrix is obtained from user experiences obtained from school pupils through interaction and helps solve the problem of cold start. The user id is used to identify all the users who log on to the system and also to identify users passed as healthy by the system.
- Malnourished user database: This is the database that stores malnourished user information after determination of malnourishment level of the user. As user supplies input on first interaction with the system, the health status of the user is derived by the rule-based inference system which will base its judgement on a standard weight-for-height table. The user id and health status of user are stored in this database and used to get the system to recommend nutritious diet to the user.
- Healthy foods/diet database: This is the repository for diets which will be recommended as system output, to help nurture a malnourished (wasted) child back to health state accepted as standard weight- for-height for the given

ISSN No:-2456-2165

age. The foods obtained here have been put together by a nutritionist with much of the foods obtainable in the western part of Nigeria (local dishes). Information on the nutrition components of foods, values for energy giving nutrients are obtained in the database.

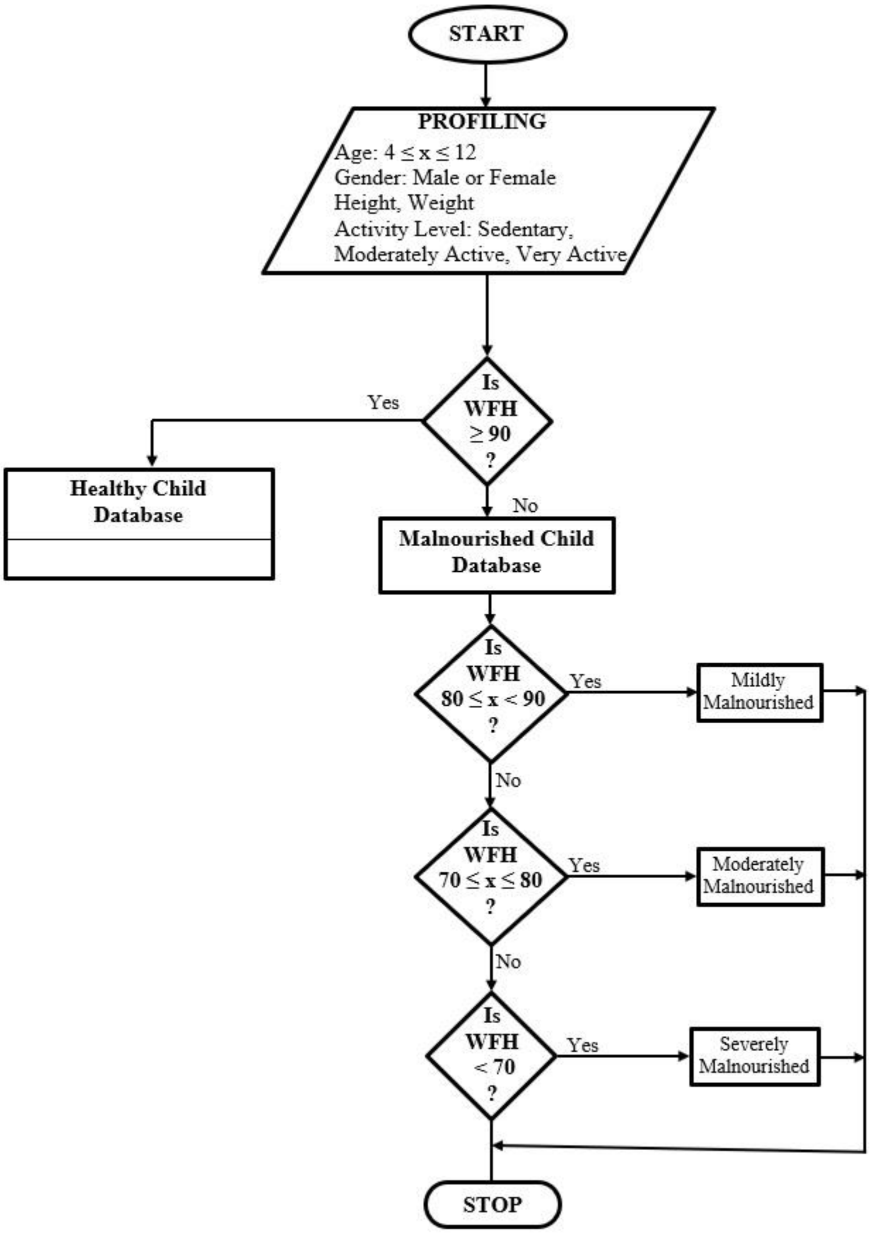

Fig 2:- Profiling Chart for the system

The representation of data in the database for the user is given as follows:

- User_Biodata [user_ID_Num, user_Name, user_age, user_gender]
- User_Anthropometric data [user_ID_Num, user_height, user_weight, user_AL]
- Diet_History [Breakfast, Lunch, Dinner].

The daily required calories are split between the three core meals of the day (breakfast, lunch and dinner) with the afternoon meal taking the highest portion of the calories as they are used more during the active hours of the child.

The system has a module that takes in child age, height, weight and activity level from which child health status is deduced. The profile module also takes in user interest and provides a platform to rate the interests from which what meal a user likes is obtained via rating score. Disliked/allergic meals are also submitted from which the system generates a substitute from the class of foods of disliked meal using the Euclidean distance metric.

A. Decision (Inference) Engine

This decides given an active user whether the user-based collaborative filtering algorithm will be used for recommendations or whether predictions will be done with the aid of the system expert nutrition module. For example, the average weight of an eight-year-old girl is 25.8kg (Disabled World, 2019). If a girl child of age eight weighs 22.6kg, the system checks the line of action to follow by dividing the weight of the child with the average weight of a healthy girl of same age and the result obtained is multiplied by 100 to get a percentage which will reflect the girl's current health status.

$$\frac{22.6kg}{25.8kg} \times 100 = 87.59\%$$

This percentage result shows that the child is mildly malnourished since a figure that lies between 80% and 89% shows mild malnutrition.

IF WFH ≥ 90 THEN
Child is Healthy
IF WFH < 90 and WFH > 80 THEN
Child malnutrition is Mild
IF WFH ≤ 80 and WFH ≥ 70 THEN
Child malnutrition is Moderate
IF WFH < 70 THEN
Child malnutrition is Severe

The system then passes control to the expert nutrition prediction module to put up a list of healthy meals that will remedy the health situation of the child; nourishing the child with nutrients that will halt wasting in the child.

If the child health status is adjudged to be healthy, the system passes control to the collaborative filtering algorithm to suggest healthy meals taken by a child of same health status and with similar food interests.

B. User-based collaborative diet recommendation

Upon the classification of a user as healthy, user-based collaborative filtering is used for prediction and recommendation of healthy meals to sustain and improve child health. Similarity between users (using cosine similarity) is obtained by comparing ratings of interests between active user and users similar to active user in interests. This measure of user similarity treats users as vectors of item ratings and then measures the cosine between vectors of two users. A value close to one indicates similarity while a value close to zero shows dissimilarity. It is obtained as:

$$s(a, u) = \sum_{j \in I} \frac{v_{aj}}{\sqrt{\sum_{k \in I_a} v_{ak}^2}} \frac{v_{uj}}{\sqrt{\sum_{k \in I_u} v_{uk}^2}} \qquad (3)$$

where v_{aj}= rating of user *a* for item *j*, v_{uj}= rating of user *u* for item *j*, v_{ak}^2= norm of rating of user *a* for each rated item, v_{uk}^2= norm of rating of user *u* for each rated item and *I*= utility matrix. The similar users with similar ratings are taken as a neighborhood according to their similarity with active user and prediction is tailored towards the likes of the user with the highest similarity score. The closer a number is to one, the higher the similarity and the farther away from one the lesser the similarity value. Based on the threshold chosen, a neighborhood of users from which recommendations will be made from is set.

In the case of a disliked food or food user is allergic to being recommended, the meal in question is marked so the user can have a choice to either change the food or not. Food subtitute is obtained by determining the Euclidean distance between the allergic food and other foods or items in the healthy foods database which fall in the same category as the disliked food. This is calculated as

$$D(Q_A, Q_B) = \frac{1}{\sqrt{N}} \left(\sqrt{\sum_{i=1}^{N} \left| q_A^i - q_B^i \right|^2} \right) \qquad (4)$$

where Q_A is the disliked meal, Q_B is the substitute meal option from the same category as disliked meal and q_A, q_B, q_C, ..., q_N are food nutrients (measured in grams) in same category as disliked food and nearest *D* is taken as substitute.

From the procedures above, the child diet recommendation system generates a seven-day meal plan that considers user food preferences and presents same to the user. Table 5 shows a sample meal plan for a healthy 8-year-old boy who is moderately active, recommended with total calories and macronutrients in each meal item. Food measurements are given in cups, ounces, slices and tablespoons.

For a disliked food, Euclidean distance between food types is computed using the macronutrient values of disliked food as basis for comparison with foods in the same family. The smaller the distance between two foods, the more likely it will be the substitute for the disliked food. With a straight line being the shortest distance between two points, the nearest food to Amala in this food class based on this will be Pupuru (Q_B), and next to that will be Pounded Yam, Garri (Eba), Fufu and Semolina in that order as shown in table 6.

Day	Breakfast (Total Calories(kcal) / MacroNutrients(g))	Lunch (Total Calories(kcal) / MacroNutrients(g))	Dinner (Total Calories(kcal) / MacroNutrients(g))	Fruits
Day 1	1c Yam (boiled) 1c Vegetable/Tomato sauce 1 Chicken Egg/ 1oz cow meat 2c Pineapple	0.75c Rice 0.75c Stew 1oz fish 1c milk	4s Bread 1Tbsp Butter 1c Milk/tea	1 banana, 0.5 Orange
Day 2	1c Beans 4s Bread 1c Milk 2c watermelon	0.75c Rice 1.5c Vegetable soup 1oz fish/meat 1c Orange Juice	1c Bean cake (Akara) 4s Bread 1c Milk 1 Tbsp Butter	1 Banana, 1 Apple
Day 3	1c Noodles 1 fried egg 1oz cow meat 1c Soy Milk	1c MoiMoi 1c Custard 1oz cow meat 1c Milk/tea	4 Slice Bread 1c Soy Milk 1 Chicken Egg 1Tbsp Butter	2 pcs of Carrot, 0.5 Apple
Day 4	1c Bean cake (Akara) 5s Bread 1c Orange Juice	0.75c Plantain (boiled) 1c Vegetable soup 1oz meat 1c Milk	0.5c Oatmeal 4 Slice Bread 1c milk 1 Egg	1 banana, 0.5 Orange
Day 5	1c Custard 0.5c milk 3s Bread 0.5Tbsp Butter	1c Fried Rice 1oz cow meat 1c milk	0.75c Rice 1c Vegetable soup 1oz fish/meat 2c Pineapple	1 Banana, 1 Apple
Day 6	1c GoldenMorn 1c milk 1c Orange Juice	1c Yam Porridge 1 oz Fish 1c Pineapple	0.75c Jollof Rice 2oz cow meat 1c milk	1banana 0.5 Apple
Day 7	1c MoiMoi 1c Custard 2oz cow meat 1c Milk/tea	0.75c Plantain (boiled) 1c Stew (tomato sauce) 1 fried egg 1oz cow meat	0.75 Medium-sized Potato (boiled) 1 oz Fish Stew 1c watermelon	1c fruit juice, Carrots

Table 5:- Recommended meal plan sample

Subset of starchy foods	Carbohydrate	Protein	Fats & Oils	E. Distance
Pounded Yam	22.21	1.03	1.42	0.9164
Pupuru	22.50	0.43	0.31	0.8136
Fufu	24.39	0.48	0.11	1.5765
Garri	22.94	0.68	0.1	0.9954
Semolina	37.97	6.61	0.55	7.5689
Amala (disliked food)	20.53	0.30	0.12	

Table 6:- Starchy foods class with distance from disliked food

C. Alternative recommendations for malnourished children

The system uses the age, weight, height, user food interests and daily required calories spread across the meals for the day, to expertly recommend meals in portions that will meet the requirements to nurse the child gradually to the weight class expected of the child. Macro food nutrients (carbohydrates, protein and fats) will constitute a major part of the meals to be recommended as they play a major role in child growth and energy supply. As the severity of wasting is assertained, the percentages of macro nutrient contents in foods recommended will be altered to meet the needs of the child.

This is done through a seven-day meal plan that can be followed till the required results are evident. The system is designed to be flexible in recommendation such that looking through recommendation history, it gives a different variety of recommendations from previous one. This ensures that the recommended meals are appealing to the user.

The activity level of the child is considered and used to recommend daily required energy that will supplement expended energy of the child. The activity level of the child (which could be sedentary, moderately active and very active) is used together with age stage of the child, gender and predetermined calorie quantities (calorie quantity required for each age stage) during recommendation process to present the foods that will carry the required calorie amount for the day.

The required daily energy (kcal) quantity will be divided into three to be spread across the three core meals taken during the day (breakfast, lunch and dinner) with the afternoon meal taking the highest portion of the calories as they are used more during the active hours of the child.

The system uses a set of produced rules considering gender, age and activity level to reach arrive at its results for the composition of food that should supply adequate amount of energy (in kilocalories) to the user. A total of 54 rules are generated to take care of the various age stages and activity levels.

IF (Gender)	AND (Age)	AND (Activity Level)	THEN (Daily Calories)
Female	4	Sedentary	1200kcal $\leq x \leq$ 1300kcal
Female	4	Moderately Active	1400kcal $\leq x \leq$ 1500kcal
Female	4	Very Active	1400kcal $\leq x \leq$ 1600kcal
Female	5	Sedentary	1300kcal $\leq x \leq$ 1400kcal
Female	5	Moderately Active	1500kcal $\leq x \leq$ 1600kcal
Female	5	Very Active	1600kcal$\leq x \leq$ 1800kcal
Female	6	Sedentary	1200kcal $\leq x \leq$ 1240kcal
Female	6	Moderately Active	1400kcal $\leq x \leq$ 1440kcal
Female	6	Very Active	1400kcal $\leq x \leq$ 1480kcal
Female	7	Sedentary	1240kcal $\leq x \leq$ 1280kcal
Female	7	Moderately Active	1440kcal $\leq x \leq$ 1480kcal
Female	7	Very Active	1480kcal $\leq x \leq$ 1560kcal
Female	8	Sedentary	1280kcal $\leq x \leq$ 1320kcal
Female	8	Moderately Active	1480kcal $\leq x \leq$ 1520kcal
Female	8	Very Active	1560kcal $\leq x \leq$ 1640kcal
Female	9	Sedentary	1320kcal $\leq x \leq$ 1360kcal
Female	9	Moderately Active	1520kcal $\leq x \leq$ 1560kcal
Female	9	Very Active	1640kcal $\leq x \leq$ 1720kcal
Female	10	Sedentary	1360kcal $\leq x \leq$ 1400kcal
Female	10	Moderately Active	1560kcal $\leq x \leq$ 1600kcal
Female	10	Very Active	1720kcal $\leq x \leq$ 1800kcal
Female	11	Sedentary	1400kcal $\leq x \leq$ 1500kcal
Female	11	Moderately Active	1600kcal $\leq x \leq$ 1800kcal
Female	11	Very Active	1800kcal $\leq x \leq$ 2000kcal
Female	12	Sedentary	1500kcal $\leq x \leq$ 1600kcal
Female	12	Moderately Active	1800kcal $\leq x \leq$ 2000kcal
Female	12	Very Active	2000kcal $\leq x \leq$ 2200kcal
Male	4	Sedentary	1200kcal $\leq x \leq$ 1300kcal
Male	4	Moderately Active	1400kcal $\leq x \leq$ 1500kcal
Male	4	Very Active	1600kcal $\leq x \leq$ 1800kcal
Male	5	Sedentary	1300kcal $\leq x \leq$ 1400kcal
Male	5	Moderately Active	1500kcal $\leq x \leq$ 1600kcal
Male	5	Very Active	1800kcal $\leq x \leq$ 2000kcal
Male	6	Sedentary	1200kcal $\leq x \leq$ 1240kcal
Male	6	Moderately Active	1400kcal $\leq x \leq$ 1440kcal
Male	6	Very Active	1600kcal $\leq x \leq$ 1680kcal
Male	7	Sedentary	1240kcal $\leq x \leq$ 1280kcal
Male	7	Moderately Active	1440kcal $\leq x \leq$ 1480kcal
Male	7	Very Active	1680kcal $\leq x \leq$ 1760kcal
Male	8	Sedentary	1280kcal $\leq x \leq$ 1320kcal
Male	8	Moderately Active	1480kcal $\leq x \leq$ 1520kcal
Male	8	Very Active	1760kcal $\leq x \leq$ 1840kcal
Male	9	Sedentary	1320kcal $\leq x \leq$ 1360kcal
Male	9	Moderately Active	1520kcal $\leq x \leq$ 1560kcal
Male	9	Very Active	1840kcal $\leq x \leq$ 1920kcal

ISSN No:-2456-2165

Male	10	Sedentary	$1360kcal \leq x \leq 1400kcal$
Male	10	Moderately Active	$1560kcal \leq x \leq 1600kcal$
Male	10	Very Active	$1920kcal \leq x \leq 2000kcal$
Male	11	Sedentary	$1600kcal \leq x \leq 1800kcal$
Male	11	Moderately Active	$1800kcal \leq x \leq 2000kcal$
Male	11	Very Active	$1800kcal \leq x \leq 2000kcal$
Male	12	Sedentary	$2000kcal \leq x \leq 2300kcal$
Male	12	Moderately Active	$2000kcal \leq x \leq 2200kcal$
Male	12	Very Active	$2300kcal \leq x \leq 2600kcal$

Table 7:- Rule base for food composition (energy (kcal))

HTML, CSS, JavaScript, PHP and MySQL are used to carry out this implementation. HTML tags are used to set up the outlook of the web pages the way they will appear in the system while CSS is used for page styling. PHP is a scripting language used for its object-oriented features and ease of use in the development of complex web applications in a relatively short period. AppServ is the local host on which the designed system is developed and programmed to run on (platform); it can also be run on the internet if hosted. The platform allows users to run web-based applications on their local computers as it were on the internet via a web browser, which is a key component of the system.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

To ascertain the effectiveness, efficiency and acceptance of the proposed system for food recommendation, the system is evaluated by technical users who are familiar with design and implementation of systems such as this; to know what user responses will be with respect to user interface and ease of use. Questions are posed to the users via the evaluate module of the system where the users are asked to rate the system usability, accuracy of recommendations and user friendliness of the system. They are also asked to rate the availability of meals in their environment and their satisfaction level as it touches system recommendation.

Figure 3 shows the evaluation module of the proposed system. A five-point Likert scale with linguistic variables (Strongly agreed, agreed, undecided, disagreed and strongly disagreed) is provided to the users to aid them in giving their responses. Users are encouraged to evaluate the system at least after a week of using the system/applying the recommendations.

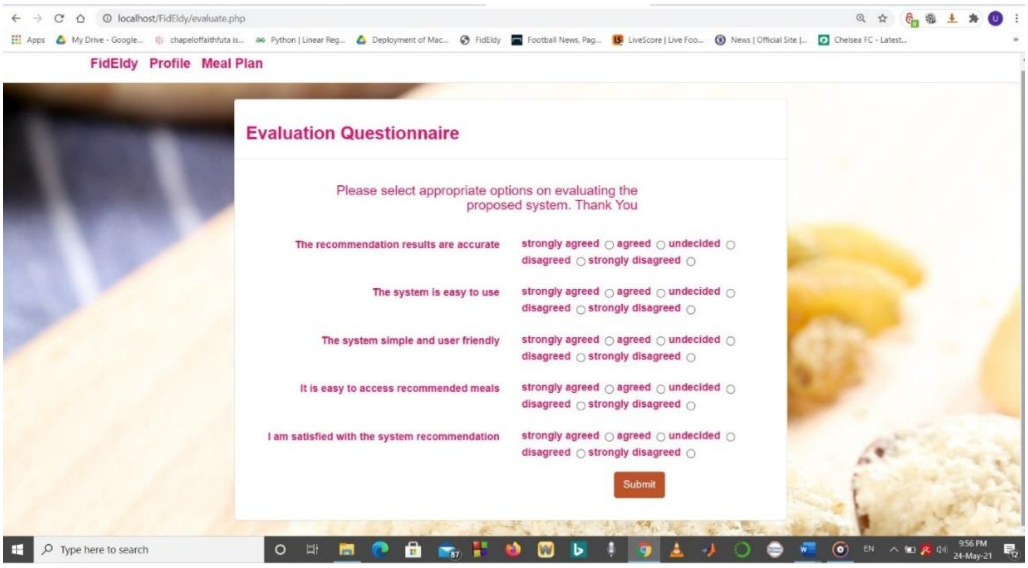

Fig 3:- System Evaluation Module

A. Evaluation Results

Table 8 shows the evaluation results of system by thirty users where SA – Strongly Agreed, A – Agreed, U – Undecided, D – Disagreed and SD – Strongly Disagreed.

Evaluation Statements	SA (%)	A (%)	U (%)	D(%)	SD(%)
The system is easy to use	22(73.33)	8(26.67)	0	0	0
The system is simple and user friendly	21(70.0)	9(30.0)	0	0	0
The recommendation results are accurate	19(63.33)	10(33.33)	1(3.33)	0	0
It is easy to access recommended meals	25(83.33)	5(16.67)	0	0	0
I am satisfied with system recommendations	22(73.33)	8(26.67)	0	0	0

Table 8:- Evaluation Results with percentage scores

ISSN No:-2456-2165

The result shows that 73.33% (22 out of 30) users strongly agree that the system is easy to use, with a further 26.67% (8 out of 30) also agreeing to ease of use. This shows the system is easy to understand by both pupils and guardians. For user friendliness which considers the user interface appearance, 70% (21 out of 30) of users strongly agree; 30% (9 out of 30) of users agree that friendliness of interface is very satisfactory. This measures up when aggregated, to satisfaction levels obtained in Barbieri et al., (2017) – 80%; and Hussain et al. (2018) – 89.7%.

For accuracy in recommendation, 63.33% strongly agree; 33.33% agree while 3.33% remain neutral. 83.33% strongly agree that recommended meals are easily obtainable. This makes system recommendations very appealing to users. For child health status, 66.67% agree that this was deduced correctly, with a further 26.67% strongly supproting while 6.67% remained neutral. For meal recommendations, 73.33% strongly agree to a high satisfaction level in meals recommended to users, with a further 26.67% also in agreement. This is higher than the average satisfaction recorded in Hussain et al. (2018). Over 70% of users believe the recommended meals can immensely imporve child health condition. This shows the proposed system to be very efficient.

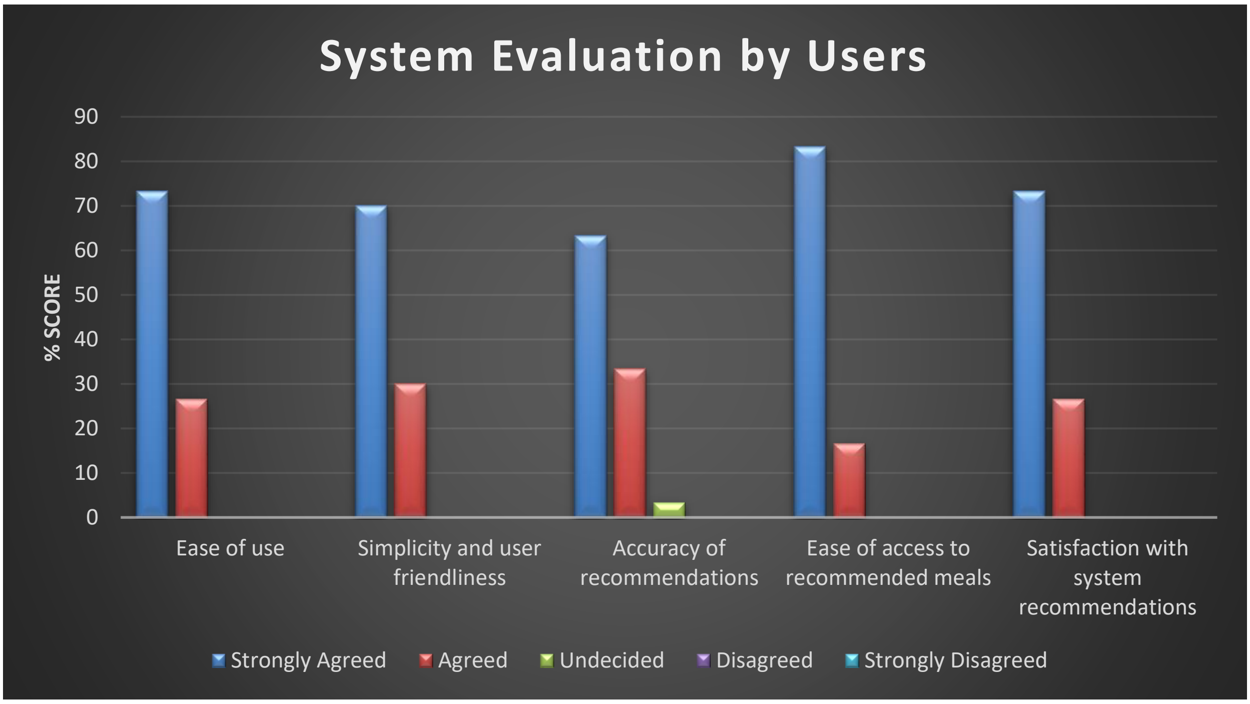

Fig 4:- Result of user evaluation of system

The system has been proven to be of high standard through its evaluation results which rate it very high in usability, friendliness, accuracy of user health status and recommendation with a high user satisfaction rate as obtained by the offline ratings of 30 initial users.

We check whether the similarity measure used is the best or most suited to the task of getting similar users. Similarity is a key building block for activities like building recommendation engines, clustering and solving classification problems. Similarity measure is the measure that proves the extent to which two objects are alike, and which portrays relationship using distance (Polamuri , 2015). A small distance means the object features have a high degree of similarity while a large distance proves dissimilarity. Polamuri (2015); Emmery (2017); Sharma (2020) give the most widely used/popular similarity measures to include Euclidean distance, Manhattan distance, Minkowski distance, Cosine similarity, Jaccard similarity and Hamming distance. We use a subset of the food matrix used for this work to test various similarity measures to know the most suitable. We extract from the dataset, the group of ten-year-old boys for the subset as shown in figure 5, implementing with Python 3.8 on Jupyter Notebook.

In [6]:
```
dfd1.head(8)
```
Out[6]:

S/N	AGE	SEX	RICE	BEANS(POTTAGE	BREAD&TEA	CORNFLAKES&MILK	COCOPOPS&MILK	BREAD&BUTTER	NOODLES
U17	10	BOY	4	4	3	3	2	2	3
U22	10	BOY	4	4	3	2	3	2	2
U28	10	BOY	2	4	3	3	3	3	4
U29	10	BOY	5	5	3	3	3	2	3
U33	10	BOY	4	2	3	3	3	3	4
U97	10	BOY	4	2	3	2	3	2	2
U118	10	BOY	4	4	3	3	2	3	3
U120	10	BOY	4	3	3	3	2	3	2

8 rows × 63 columns

Fig 5:- filtered group of ten-year-old boys

We pick the first six children from the group as a subset which we build a similarity analysis on while dropping the columns for Age and Sex as shown in figure 6.

In [12]:
```
df
```
Out[12]:

	Beans	Bread&tea	Cornflakes	Cocopops	Bread&butter	Eba&Egusi
U17	4	3	3	2	2	3
U22	4	3	2	3	2	1
U28	4	3	3	3	3	2
U29	5	3	3	3	2	4
U33	2	3	3	3	3	4
U97	2	3	2	3	2	4

Fig 6:- subset of the boys' filter for analysis

First, the user ratings are represented as vectors by specifying the row number (example X[0]) and the column size (example X[:6]) for each user and the output is a list that contains the ratings for each user. This is used for computing the several similarity measures.

In [14]:
```
#representing the user ratings as vectors, we have
U17 = X[0][:6]
U22 = X[1][:6]
U28 = X[2][:6]
U29 = X[3][:6]
U33 = X[4][:6]
U97 = X[5][:6]
#which when printed, gives the ratings as lists
print(" U17:",U17,"\n U22:",U22,"\n U28:",U28,"\n U29:",U29,"\n U33:",U33,"\n U97:",U97)
```
```
U17: [4 3 3 2 2 3]
U22: [4 3 2 3 2 1]
U28: [4 3 3 3 3 2]
U29: [5 3 3 3 2 4]
U33: [2 3 3 3 3 4]
U97: [2 3 2 3 2 4]
```

Fig 7:- converting ratings to lists

Cosine similarity: The cosine similarity metric finds the normalized dot product of the two attributes and when determined, cosine similarity effectively finds the cosine of the angle between the two objects (Polamuri, 2015). It treats users as vectors of item ratings and then proceeds to measure the cosine between the vectors of two users (Breese et al., 1998). The function for cosine similarity is given and used to calculate the similarity between users as shown below. A value close to one shows more similarity than a value closer to zero. From the results obtained (figure 11), cosine similarity clearly considers the ratings of the users and as seen in the results, user 28 and 29 are not identical in similarity as given by other measures. In fact, with cosine similarity measure, we see that all users are different in their rating of meals. User 29 is much more similar to U17 than U28 since it scores the highest similarity of all the users and this makes it ideal for use in establishing user similarity.

This analysis shows why cosine similarity has been adopted for establishing user similarity in this work. Table 9 shows the comparison of various similarity metrics.

User 17 With	Similarity Measures			
	Euclidean Distance	Manhattan Distance	Jaccard Similarity	Cosine Similarity
U22	2.4495	4	0.75	0.9396
U28	1.7321	3	1.0	0.9730
U29	1.7321	3	0.75	0.9901
U33	2.6458	5	1.0	0.9356
U97	2.6458	5	1.0	0.9290

Table 9:- Similarity metrics evaluation

This validates cosine as the similarity metric of choice for this work as it recognizes each user distinctly from others.

V. CONCLUSION AND FUTURE DIRECTION

Healthy nutrition provided for a growing child is one of the best gifts a child could ever receive in its formative years as this will aid and improve growth, body formation, healthy bones, strong immune system, and enhanced learning ability while giving the child a great chance of making the most of life. A diet recommendation system for school-aged children has been developed to battle the scourge of malnutrition, particularly low weight-for-height. The system has been shown to be efficient in diet recommendation. School feeding programmes and homes/families can use this system to enhance their food quality for children. Future additions to the work could include tailoring system to service users from other regions; and creating an avenue where a user can access a nutrition expert on the system in real time using voice over internet protocol.

REFERENCES

[1]. Avencena, I. T., & Cleghorn, G. (2014). The Nature and Extent of Malnutrition in Children. *Reseach Gate*, 1 - 11.
[2]. Barbieri, L., Bruno, F., & Muzzupappa, M. (2017). Virtual museum system evaluation through user studies. *Journal of Cultural Heritage*, 1 - 8.
[3]. Breese, J. S., Heckerman, D., & Kadie, C. (1998). Empirical analysis of predictive algorithms for collaborative filtering. *Fourteenth conference on Uncertainty in artificial intelligence (UAI' 98)* (pp. 43 - 52). Madison, Wisconsin: Morgan KAufmann Publishers Inc. San Francisco, CA, USA.
[4]. Brown, J. L., & Pollitt, E. (1996). Malnutrition, Poverty and Intellectual Development. *American Scientific*, 1 - 7.
[5]. Coleman, E. (2018). *Nutrition Requirements For School Age Children.* Retrieved from SF GATE: https://healthyeating.sfgate.com/nutrition-requirements-school-age-children-3781.html
[6]. Collins, C. E., Watson, J., & Burrows, T. (2010). Pediatric Review: Measuring dietary intake in children and adolescents in the context of overweight and obesity. *International Journal of Obesity*, 1103-1115.
[7]. De Pessemier, T., Dooms, S., & Martens, L. (2013). A Food Recommender for Patients in a Care Facility. *Proceedings of the 7th ACM Conference on Recommender Systems (RecSys 2013)* (pp. 209 - 212). Hong Kong: Presented at the 7th ACM Conference on Recommender Systems (RecSys 2013).
[8]. Department of Health. (1991). *Dietary Reference Values for Food Energy and Nutrients for the United Kingdom. Report on Health and Social Subjects No 41.* London: HMSO.
[9]. Disabled World. (2019, May 15). *Average Height to Weight Chart - Babies to Teenagers.* Retrieved from Disabled World: https://www.disabled-world.com/calculators-charts/height-weight-teens.php
[10]. Elahi, M., Ge, M., Ricci, F., Massimo, D., & Berkovsky, S. (2014). Interactive Food Recommendation for Groups. *Poster Proceedings of the 8th ACM Conference on Recommender Systems (RecSys 2014).* Foster City, Silicon Valley, USA: CEUR Workshop Proceedings.

[11]. Elsweiler, David; Harvey, Morgan; Ludwig, Bernd; Said, Alan. (2015). Bringing The "Healthy" Into Food Recommenders. *2nd International Workshop on Decision Making and Recommender Systems, DMRS 2015. 1533*, pp. 33 - 36. Bozen-Bolzano, Italy: CEUR Workshop Proceedings. Retrieved from http://ceur-ws.org/Vol-1533/

[12]. Emmery, C. (2017). *Euclidean vs. Cosine Distance.* Retrieved from GitHub: https://cmry.github.io/notes/euclidean-v-cosine

[13]. FAO. (2013). *The State of Food And Agriculture.* Food And Agriculture Organization Of The United Nations. Retrieved from http://www.fao.org/docrep/018/i3300e/i3300e.pdf

[14]. FARE. (2016). *Food Allergy: Facts and Statistics*. Retrieved October 17, 2019, from Food Allergy Research and Education: https://www.foodallergy.org/life-with-food-allergies/food-allergy-101/facts-and-statistics

[15]. Ferreira, H. d. (2020). Anthropometric assessment of children's nutritional status: a new approach based on an adaptation of Waterlow's Classification. *BMC Paediatrics*, 1 - 5.

[16]. Ge, M., Elahi, M., Fernaandez-Tobias, I., Ricci, F., & Massimo, D. (2015). Using Tags And Latent Factors In A Food Recommender System. *5th International Conference on Digital Health 2015* (pp. 105 - 112). Florence: Proceedings of the 5th International Conference on Digital Health 2015.

[17]. Hazman, M., & Idrees, A. M. (2015). A Healthy Nutrition Expert System for Children. *The 5th IEEE International Conference on E-Health and Bioengineering - EHB 2015.* Iaúi, Romania: IEEE.

[18]. HER. (2015). Recommendations For Responsible Food Marketing To Children (Building Evidence To Prevent Childhood Obesity). *Healthy Eating Research*. Retrieved from www.healthyeatingresearch.org

[19]. Hussain, J., Hassan, A. U., Bilal, H. M., Ali, R., Afzal, M., Hussain, S., . . . Lee, S. (2018). Model-based adaptive user interface based on context and user experience evaluation. *Journal on Multimodal User Interfaces*, 1-16.

[20]. Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). Recommendation systems: Principles, methods and evaluation. *Egyptian Informatics Journal*.

[21]. Kale, A., & Auti, N. (2015). Automated Menu Planning Algorithm for Children: Food Recommendation by Dietary Management System using ID3 for Indian Food Database. *2nd International Symposium on Big Data and Cloud Computing (ISBCC'15)* (pp. 197 - 202). Chennai, India: Procedia Computer Science.

[22]. Mandal, A. (2019). *What is malnutrition?* Retrieved from News Medical Life Sciences: https://www.news-medical.net/health/What-is-malnutrition.aspx

[23]. Mustafa, N., Abd Rahman, A. H., Sani, N. S., Mohamad, M. I., Zakaria, A. Z., Ahmad, A., . . . Safii, N. S. (2020). iDietScore: Meal Recommender System for Athletes and Active Individuals. *International Journal of Advanced Computer Science and Applications*, 269 - 276.

[24]. Padmapritha, T., Subathra, B., Ozyetkin, M. M., Srinivasan, S., Bekirogulu, K., Kesavadev, J., . . . Sanal, G. (2020). Smart Artificial Pancreas with Diet Recommender System for Elderly Diabetes. *IFAC Papers Online*, 16366 - 16371.

[25]. Phalen, J. A. (2013). Managing Feeding Problems and Feeding Disorders. *Paediatrics in Review*, pp. 549-556.

[26]. Polamuri , S. (2015). *Five Most Popular Similarity Measures Implementation in Python*. Retrieved from Dataaspirant: https://dataaspirant.com/five-most-popular-similarity-measures-implementation-in-python/

[27]. Princy, J., Senith, S., Kirubaraj, A. A., & Vijaykumar, P. (2021). A Personalized Food Recommender System for Women Considering Nutritional Information. *International Journal of Pharmaceutical Research*, 1884 - 1887.

[28]. Rehman, F., Khalid, O., Haq, N. u., Khan, A. R., Bilal, K., & Madani, S. A. (2017). Diet-Right: A Smart Food Recommendation System. *KSII TRANSACTIONS ON INTERNET AND INFORMATION SYSTEMS*, 2910-2922.

[29]. Sharma, P. (2020). *4 Types of Distance Metrics in Machine Learning.* Retrieved from Analytics Vidhya: https://www.analyticsvidhya.com/blog/2020/02/4-types-of-distance-metrics-in-machine-learning/

[30]. Sharma, R., & Singh, R. (2016). Evolution of Recommender Systems from Ancient Times to Modern Era: A Survey. *Indian Journal of Science and Technology*, 1 - 12.

[31]. Thomas, L. (2018). *how fast food affects children's health.* Retrieved from news medical.net: http://www.news-medical.net

[32]. Trattner, C., & Elsweiler, D. (2017). Food Recommender Systems Important Contributions, Challenges And Future Research Directions. 1 - 16.

[33]. Tyessi, K. (2018). *Nigeria: Stunting, Wasting, Underweight Prevalence Increases in Children Says Mics.* Retrieved from All Africa: https://allafrica.com/stories/201807260597.html

[34]. Ueta, T., Iwakami, M., & Ito, T. (2011). A Recipe Recommendation System Based on Automatic Nutrition Information Extraction. *International Conference on Knowledge Science, Engineering and Management KSEM 2011. 7091*, pp. 79 - 90. Springer, Berlin, Heidelberg. doi:https://doi.org/10.1007/978-3-642-25975-3_8

[35]. UNICEF; WHO; WorldBankGroup. (2017). LEVELS AND TRENDS IN CHILD MALNUTRITION. (UNICEF, WHO, & WorldBankGroup, Eds.) *Joint Child Malnutrition Estimates: Key findings of the 2017 edition*, pp. 1-14.

[36]. Waterlow, J. C. (1973). The Assessment and Classification of Protein-Energy Malnutrition in CHildren. *The Lancet*, 87 - 89.