Unhealthy dietary behavior based user life-log monitoring for wellness services

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Abstract. Unhealthy behavior, constitutes of unhealthy diet, smoking, physical inactivity and alcohol intake, increases the risk of chronic diseases and premature mortality. These unhealthy behaviors can be avoided by little intention and guidance. Diet is an influential factor of healthcare .Healthy and balanced diet selection is related to the better life expectancy and decreases the chances of chronic diseases. The Ubiquitous computing revolutionized the wellness domain towards user centric preference based health management. In this study we proposed a method for monitoring and indication of users' unhealthy nutrition consumption. We evaluated 3 different timings of indication to user for induction of healthy dietary pattern. The "location and time based indication" depicts very promising result of 78% in the adoption of healthy diet pattern and has positive impact on the intake of fat nutrient in diet.

Keywords: Life-log, automatic monitoring, unbalanced diet, unhealthy situation, wellness.

1 Introduction

Today in wellness domain, technology focuses to improve personal health and socio-economic conditions through self –quantification from innovative and smart gadgets. According to theoretical model, wellness was introduced in 1990s [1], [2] as Wheel of Wellness. The initial high level wellness models were defined and categorized into nutrition knowledge, stress management, physical fitness and environmental & social awareness [3]. The wellness is a concerning target of healthcare domain to avoid and prevent the diseases with the development of innovative user centric platform. The platforms are capable to digitize health and wellness domain and provide wellbeing services and recommendations [4]. Good physical health, proper food, freedom to live, social interaction and safety define the human wellbeing [5]. So active routine, balanced diet, proper hydration, leisure and finance are ingredients of healthy lifestyle [6].

1.1 Consequences of Unhealthy Behavior

Multiple research have shown that specific unhealthy behaviors, including smoking, physical inactivity, higher alcohol intake and, unbalanced diets are associated with an increased risk of cardiovascular disease, cancer and premature mortality [7]. Practicable improvements in lifestyle behaviors are likely to have a significant impact at both the individual and population level. The health status of the population can simply be measured from mortality rate, where unhealthy behaviors have been associated with a higher risk of lifestyle diseases [8]. Diet is an influential health agent and bad diet pattern is among the prominent causes of premature death and chronic disease [9]. The diet constitutes of multiple nutrients in different proportions. It is quite difficult to calculate multiple attribute to all variations in dietary pattern. According to the FSC (Australia New Zealand Standards Code) [16] the recommended balanced diet for an average adult is as shown in Table. 1.

Table 1. Nutrition requirements of average adult

	Component	Quantity Per Day
Average Adult-Requirements	Energy	2000 Calories
	Protein	50 grams
	Fat	70 grams
	Carbohydrates	310 grams
	Sugars	90 grams
	Sodium (salt)	2.3 grams
	Dietary Fiber	30 grams

1.2 Wellness Applications for Human Activity Analysis

Currently, the designing trend of healthcare and wellness applications changes to manage and analyze the users' temporal activity data to identify healthy and unhealthy lifestyle pattern [11]. The identified patterns may help to understand and diagnose the root cause of any undesired health issues. Instead of reactive approach to cure and manage diseases, these applications are focusing on proactive personalized health approach. Multiple ubiquitous applications are available i.e. 7 Minute Workout, LoseIt, Noom Coach and etc. These applications are used to quantify and log user activities, and calories consumption to empower users for visualization. In the upcoming portions we have discussed Mining Minds platform, Nutrition focused lifelog monitor architecture and evaluation methodology.

2 Mining Minds: In a Nutshell

Context based health informatics is a fruit of technology revolution for community [14]. The emerging software technology has reshaped the world through big data infrastructure and deep learning techniques to analyze the buried pattern under pile of data. Our ongoing project, Mining Minds MM [11], [12] is providing a platform to educate, engage and trigger the users on the basis of preferences and context to support for leading long healthy lifestyle. It is possible because of the use of state of the art technologies and emerging electronic gadgets. The concepts, from curation of raw sensory data to services orchestration, make the platform capable to manage the current requirements of user centric model in healthcare and wellness domains [13].

Mining Minds platform provides interface to communicate and gather multimodal data generated from different sensors to capture the temporal and spatial information along with activities. The key attributes time, place and activity are used to understand the user context and support to generate context based personalized wellness recommendations [12]. To cope with the challenges of personalized wellness, platform consists of five layers Data Curation Layer (DCL), Information Curation Layer (ICL), Service Curation Layer (SCL), Knowledge Curation Layer (KCL) and Supporting Layer (SL) respectively.

The SL is in-charge of the interaction with users and providing analytical reports on the basis of customer's requirement in a graphical manners. The granularity of analytics depends on the access level permission of users. Comprehensive view of the habits, activities and classification is provided to wellness stakeholders on the demand base and access right to understand and make decision for improvement [14], [15].

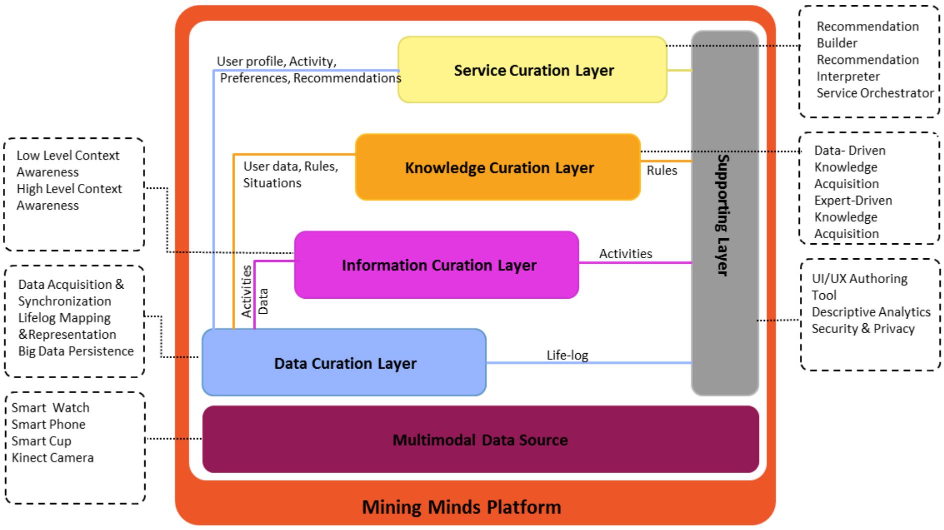

Fig. 1. Mining Minds Platform

The SCL is the orchestrator of personalized recommendation services in push and pull mode. In push mode the indication for recommendation is generated by platform while in pull mode the user requests for recommendations. The knowledge based personalized recommendation are provided by exploring demographic, physiological, health status, context and preferences information [14].

The KCL provides a data driven and an expert driven knowledge acquisition authoring environment to expert. Experts can transform their experiences and wellness knowledge in to rules through authoring environment. These rules guide about the unhealthy context based situation in the life-log and provide remedies to avoid unhealthy patterns in term of actions [15]. So the rules are then transformed into executable guidelines to highlight monitoring situations and the recommendation for action plan. Besides authoring environment the experts are supported through data driven approach which consists of machine learning algorithm to facilitate through previous information and knowledge.

ICL recognize user's activities and context from multimodal sensory data through hierarchical models. It consists of multiple recognizers for activity, emotion and location respectively. These recognizers provides the low level context awareness. The fusioning of low level context supports to recognize various high level context. It is the essential layer of MM platform to manage the activity context, e.g. sitting in office. These low level and high level contexts play an essential role for defining the lifestyle pattern [15].

DCL is the foundation service in the MM platform. It provides the ability to continuously sense and manage the raw sensory data from multimodal data sources. The data acquisition is device independent and can support large induction of sensors which helps to identify richer context [4]. It provides data curation through data acquisition and synchronization, data representation and mapping and big data storage processes [14].

Monitoring of life-log is to find out the existence of an unhealthy situation in the current activities of user on the basis of expert provided situations. These situations are provided by expert using the rule authoring capabilities of KCL e.g. eating fats more than requirement. We proposed a monitoring architecture to search out realtime unhealthy situation. It has an ability to filter out the alarming situations based on the context and conditions defined by nutritionist, intimate the wellness service at real time and provide information for descriptive analytics.

3 Nutrition Focused Life-log Monitor Architecture

Current wellness applications recognize the user activities, log them and represent in an interactive graphical manner [11]. In addition to present the user's activities logs, a range of applications also provides the impact of co-related activities on health and recommendations [10]. It is more beneficial to indicate the unhealthy nutritional habits to the healthcare stakeholders which may help them to avoid their bad impact. The proactive approach towards healthy lifestyle drive us to construct a nutrition focused Life-log Monitor (LLM). The LLM, shown in Fig. 2, constitutes of three major components. These components manage the rules related to unhealthy habits provided by experts, monitor the life-log under the guidance of these rules and indicate the wellness services instantly. The three main components are Monitor Event Configurator, Constraints Configurator and Situation Event Detector.

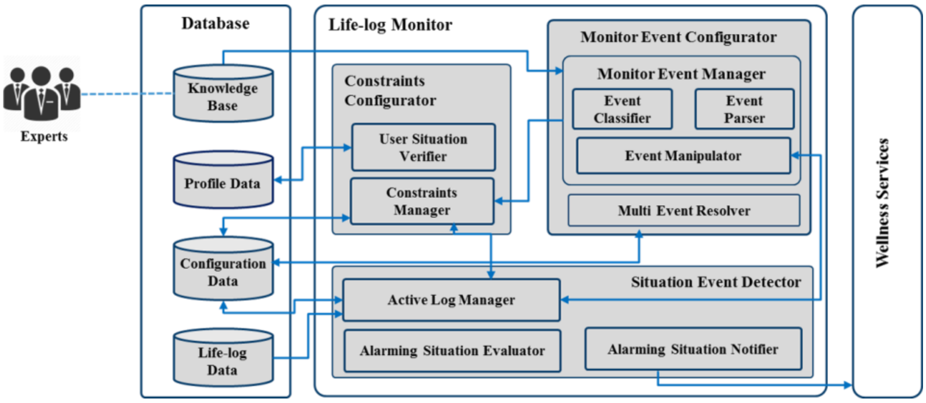

Fig. 2. Nutrition focused Life-log Monitor Architecture

3.1 Monitor Event Configurator

Nutritionists are the expert to provide guidelines for identification of the alarming micro nutrition intake with respect to the context of the user. These guidelines are authored through authoring environment and share in common configuration format. The monitor event configurator is responsible for extracting the monitoring situations from a common configuration format as shown in Fig. 3. The situations are parsed and classified into monitoring situations and situation constraints. The monitoring situation constitutes of nutrition and its quantity for a particular day. The Event manipulator map the monitoring situation in configuration data for further access.

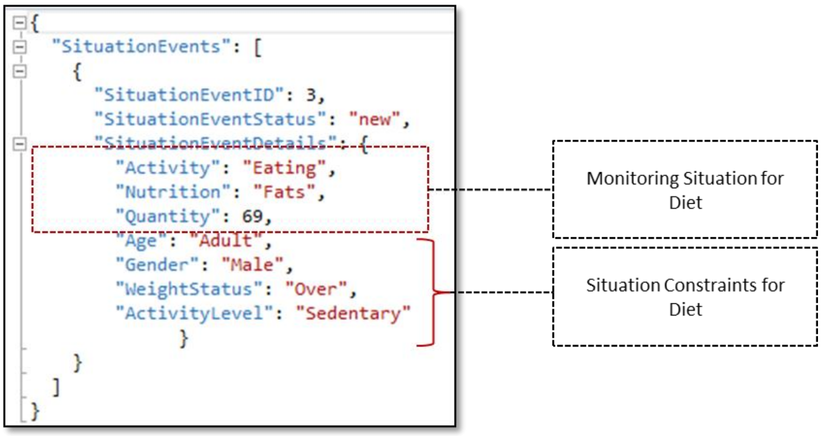

Fig. 3. Common configuration format for complete Situation

Nutrition monitoring situation consist of information related to activity, type of nutrition and the quantity of nutrition required daily. The rest of the part defines the constraints that are related to the situation and support to highlight the context of the situation.

3.2 Constraint Configurator

Constraints of a particular monitor-able situation are essential to understand the context in which monitoring is required as shown in Fig. 3. If the constraints are not satisfied, then there is no need to monitor those situations. The constraint configurator not only manages the constraint portion but also verifies the situation's constraint at real time.

The constraint manager manages the constraint portion into configuration database for further usage. It stores the constraints in key-value pair format to maintain the dynamicity for handling multiple constraints.

The User Constraint Verifier (UCV) is activated whenever a monitor-able activity is detected. It searches the user profile to verify the constraints to satisfy the context of the situation. It communicate all those situations whose context are matched for further detection and monitoring.

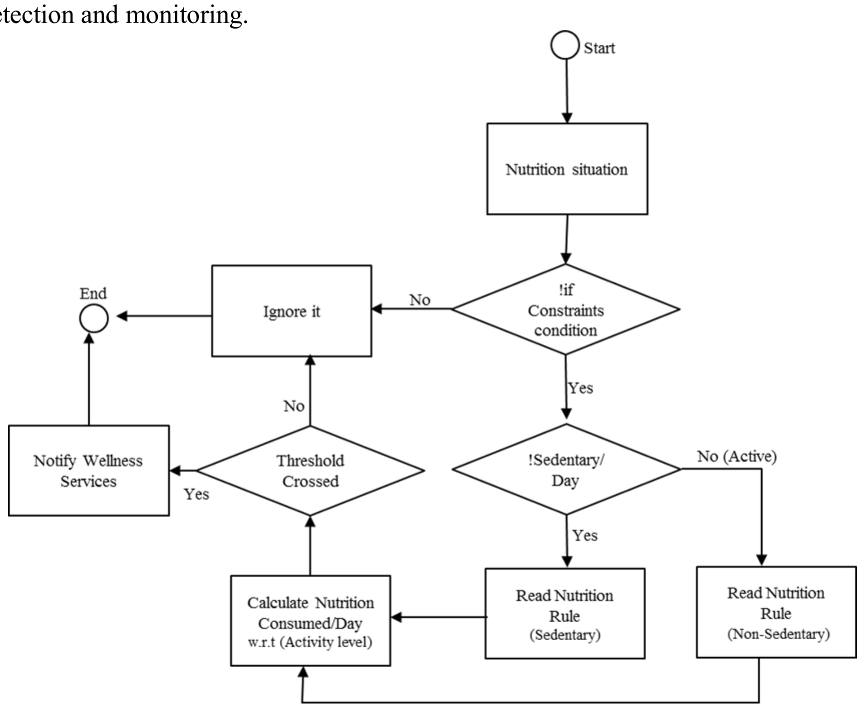

Fig. 4. Flow chart of Life-log Monitoring

3.3 Situation Event Detector

The identification of an unhealthy diet depends on the intake of the amount of nutrients in a whole day till current time. Monitoring of such situation is performed by

Situation Event Detector (SED), which is key component of the LLM. It identifies the situation when amount of nutrients cross the threshold values with respect to some context. These situations are identified by the guidelines provided by the expert in the form of rules. The situation detection task is performed by Alarming Situation Evaluator (ASE) which map the intake nutrients with the defined target. While indication in a particular communication format is performed by the Alarming Situation Notifier (ASN).

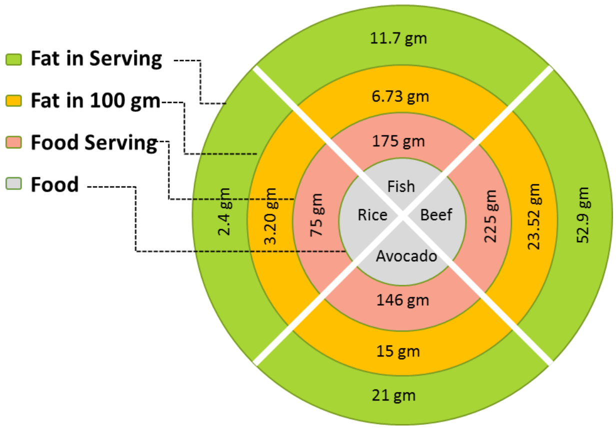

Fig. 5. Amount of Nutrient serving

ASE identify the abnormal nutrition situation by comparing the quantity of nutrition accumulated in the whole day as shown in Fig. 4. For the accumulation of nutrients we used the information extracted by the guide lines of United States Department of Agriculture [18]. It provides about the amount of nutrient per 100 gm of food. It converted nutrient amount into serving amount with the help of information extracted about serving [19] as shown in Fig. 5.

It also perform analysis of user behavior in-term of sedentary or active in a particular day as per the information extracted from Canadian Physical Activity guidelines [17] as shown in Fig. 6. The ASE handover the unhealthy nutrition situation to ASN for the conversion of the nutrition and user information into common communication format and send it to the wellness services for indication and recommendations.

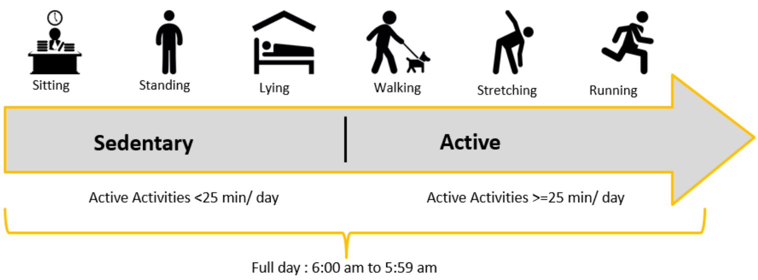

Fig. 6. Activities for Behavior Identification

4 Evaluation Methodology

To evaluate the indication for nutrition in real environment, we enhanced our previous work of activity monitoring to nutrition monitoring and integrated it with Mining Minds platform. The MM platform has provided the service of logging food through picture and tag. The user can take food picture and sends to the mining minds platform with food tag. Our database contains 2055 food items with their serving amount of nutrients. In this evaluation we focused particularly on the amount of fat nutrient required by a person and intake of it. The nutrition monitoring component manipulate the food nutrient for maintaining the log and nutrient consumption in a particular day.

4.1 Experimental Setup

In this work we are considering the eating activity for nutrition monitoring along with physical activities, so that we can validate monitoring of nutrition quantity intake for two different kinds of user i.e. the sedentary and the active one. We have 10 adult volunteers of different ages and gender. All of them have different height and weight. Through BMI calculation we can see there are three main groups of people on the basis of weight, as shown in Table. 2.

Table 2. Volunteers Detail involved in Experiment

Subject	Age	Gender	Height(cm)	Weight (kg)	BMI	Weight Status
S1	33	Male	178	92	29	Over
S2	27	Male	173	73	24.4	Normal
S3	28	Female	168	72	25.5	Over
S4	29	Female	164	56	20.8	Normal
S5	24	Male	179	69	21.5	Normal
S6	25	Male	176	75	24.2	Normal
S7	24	Male	165	48	17.5	Normal
S8	28	Female	165	64	23.5	Normal
S9	23	Male	165	66	24.2	Normal
S10	39	Male	180	86	26.5	Over

The Mining Minds platform has high accuracy to identify different activities: sitting, standing, lying, walking, stretching, running and eating [15]. Our nutrition expert provides the amount of nutrition required in different groups of people. The adults can be divided into 12 groups on the basis of gender, weight status, and activity level with the recommended fat amount (gm) per day as shown in Table. 3.

Table 3. Situations for Monitoring the Activities

Sr.#	Age Group	Gender	Weight Status	Activity Level	Recommended Fat
1	Adult	Male	Over	Sedentary	69 gm
2	Adult	Male	Over	Active	72 gm
3	Adult	Male	Normal	Sedentary	70 gm
4	Adult	Male	Normal	Active	82 gm
5	Adult	Female	Over	Sedentary	60 gm
6	Adult	Female	Over	Active	70 gm
7	Adult	Female	Normal	Sedentary	66 gm
8	Adult	Female	Normal	Active	78 gm
9	Adult	Male	Under	Active	85 gm
10	Adult	Female	Under	Active	74 gm
11	Adult	Male	Under	Sedentary	69 gm
12	Adult	Female	Under	Sedentary	61 gm

We have recorded the activities of the volunteers as a whole for 3 weeks with minimum of 4 days in a week. The indication is provided on the basis of food that they logged and the location detection with respect to time.

4.2 Evaluation Criteria

The performance of the LLM is monitored on the basis of the feedback gathered from the volunteer as well as the log saved by them regarding the fat intake a whole day. These volunteers are students, about 30% enjoy their meals in the lab and rest take meal either at home or restaurant. The timing for the breakfast is between 7:00 am to 10:00 am, for lunch is 12:00 pm to 3:00 pm and for dinner is 6:00 pm to 10:00 pm.

In the 1st week duration MM platform only recorded the food log without creating any indication and recommendation of food. In this duration volunteers had recorded all the food stuff that they took in the whole day. The breakfast, lunch and dinner were recorded very well but there was issue regarding other supplementary food stuff (like chocolates, biscuits, chips). In next 2 weeks, LLM started monitoring and indicated the volunteers about the food on the basis of required fats and fats already consumed by them. The indication is produced to the wellness service whenever the amount of nutrient particularly fats crossed threshold value for a particular day i.e. 6:00 am to 5:59 am. Moreover if the amount of nutrient crossed the threshold value with a particular meal then after that indication is also generated.

4.3 Experimental Result Analysis

LLM starts monitoring of the nutrients as soon as user logged the food. It manipulates the physical activity status of the user to identify the sedentary or active status. Then check for the threshold with respect to the category of user for nutrient. We have evaluated the effectiveness of indication in three different scenarios:

i) Start of Meal time,
ii) Food Logging time,
iii) Location and Meal time based

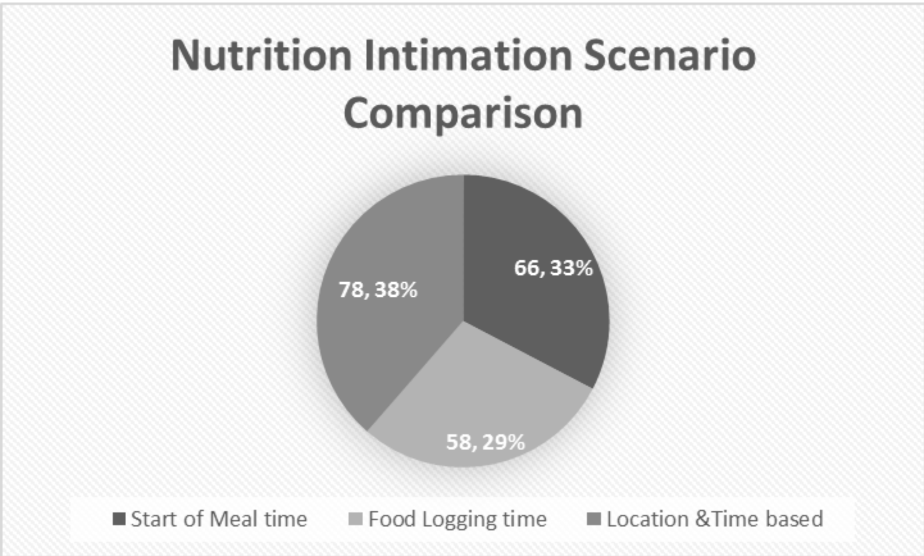

Fig. 5. Nutrition Intimation Scenario Comparison

After analysis of the food log, it is observed that the indication of nutrition on the basis of location and time is quite effective as shown in Fig. 5. While the indication at the food logging time is the least effective. According to the volunteers' feedback, they have to remember about the food recommendation for long period of time. According to the analysis, we divided the volunteers into 3 categories which were overweight, normal weight and underweight groups and all of these were under the category of sedentary activity level. The result shows that there is an impact of indication that improved the intake of fats amount of all three categories, but the change in overweight category is little higher as shown in Fig. 6.

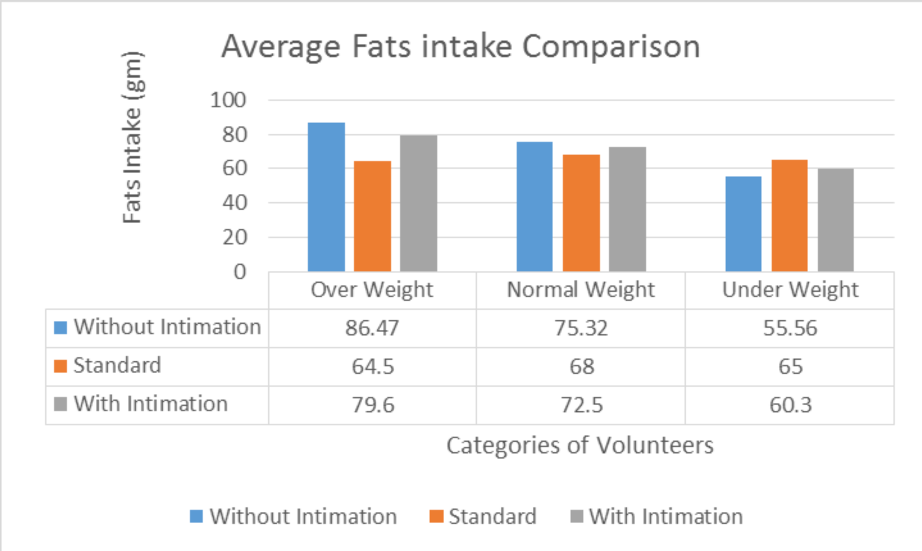

Fig 6. Fats Intake Comparison Chart

5 Conclusion and Future Work

The designed LLM monitors the fat nutrient and indicate about the target values to the user recommended by the expert rules. The push based methodology of indication supports the users to adopt healthy dietary behavior proactively. It is a new approach to monitor nutrition and push information instead of waiting for the user or expert to examine the daily diet. This technique can support the wellness applications to become proactive to avoid the bad impact of unhealthy behavior. The precautionary approach can be adopted for more effective way to reduce weight and maintain balanced diet for longer period. Currently, the LLM monitors diet for sedentary and active adult persons with respect to gender and weight status. In wellness domain the diet has a big influence on diabetic, cardiac and hypertensive patients. In future we will extend the LLM for monitoring and intimating the dietary pattern for chronic disease patients.

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