HHS Public Access
Author manuscript
Proc Int Conf Image Anal Process. Author manuscript; available in PMC 2019 May 22.

Published in final edited form as:
Proc Int Conf Image Anal Process. 2017 September ; 10590: 444–452.

Pocket Dietitian: Automated Healthy Dish Recommendations by Location

Nitish Nag, **Vaibhav Pandey**, **Abhisaar Sharma**, **Jonathan Lam**, **Runyi Wang**, and **Ramesh Jain**
University of California, Irvine, USA

Abstract

A root cause of chronic disease is a lack of timely informed decision power in everyday lifestyle choices, such as in diets. Users are unable to clearly delineate and demand healthy food in a quantitative manner. To scale the benefit of health nutrition coaching in broad real-world scenarios, we need a technological solution that is constantly able to interpret nutrition information. We ingest nutritional facts about products to efficiently calculate which items are healthiest. We deliver these results to users based on their location context. Our ranking algorithm outperforms major nutrition score metrics, and is more consistent than human dietitians in real world scenarios. Most importantly, our system gives the user a rapid way to connect with healthy food in their vicinity, reducing the barriers to a healthy diet.

Keywords

Cybernetics; Precision medicine; Disease prevention Context awareness; Mobile health; Personalized; Nutrition Expert systems

1 Introduction

Health is essentially a product of our genome and lifestyle [12]. Dietary choices are a major component of lifestyle and can have great impact on an individual’s long term health outcomes.

US federal nutrition guidelines (Fig. 1) are hard to translate into everyday life decisions. Although the knowledge exists, it is not in an actionable form. For example, typically patients with diabetes who are supervised by nutrition experts meet once every three months. Even if a nutritionist is available to guide a client, they don’t usually have all information related to the appropriate nutrition in immediate context of the individual.

Real-time *multimedia* technologies will play a major role in powering recommendations to solve health issues. Leading medical professionals have advocated for a deeper integration of technology into health care [12]. Patients make better lifestyle choices that would combat diabetes if given guidance [11]. Ultimately, transforming data and knowledge to actionable

nagn@uci.edu.

lifestyle choices is the most promising, effective, and attainable method to improve human health. We have developed a system that can place a dietitian level of decision support for finding food within a location aware automated smartphone application.

Of all the food consumers eat, now more than half comes from eating out, with the future trend toward increasing food purchases made out. Assisting everyday lifestyle management must be inexpensive, scalable, and increase health transparency of consumer purchasing. This is especially important to reach all ends of the socioeconomic spectrum [9]. Companies like Amazon use quantitative measures like reviews or filters to help customers easily find what they are looking for at the correct granularity of the product. The essential question we want to answer for every consumer is: “How will this product affect my health?”. At the moment, labels on products falsely claim how “healthy” a product is, but consumers do not trust companies to give them an honest depiction of their product. We aim to develop a third party platform that can independently judge the health metrics given product specifications.

Recommendations via expert knowledge are the key to unlock healthy diets for the world. Multimedia work in this field has primarily focused on giving the user figures and statistics of past data. Tracking diet is a very useful feature, but lacks the capability of giving actionable suggestions to improve health. The core problem at hand we are attempting to solve is real time needs-resource matching. Recommendations are essential to modern content and product consumption. Ultimately this system effortlessly connects a tasty and healthy meal to the consumer, which is the key to driving behavior change for healthier lifestyles.

2 Related Work

Better lifestyle management is appreciated as a win-win-win factor by patients, providers, and insurance entities. Programs like the Diabetes Prevention Program (DPP) have been approved by the National Institute of Health in the United States for health insurance reimbursement codes for over 100 million patients.

Socioeconomic factors prevent most people from access to private dietitians. Furthermore, even those with health insurance are only reimbursed if they are at high risk or diseased, which is too late. Practicing Registered Dietitians, PhD researchers with diabetes clients, Certified Diabetes Educators, and nutritionists all spend significant amounts of time trying to help recommend what their clients should eat. These providers spend most of their interaction time with clients also trying to understand their dietary habits. This can be streamlined through intelligent diet tracking from transactions that take place from the recommendations and image understanding, potentially reducing visit times by 30–45%. There have been large research efforts by nutrition experts to try and grade the quality of food. Qualitative approaches include the Healthy Eating Index and the Diet Quality Index are semi-quantitative [5]. From these methods, nutritionists have vocalized the need to translate expert recommendations into a usable platform for simple consumption by users [7]. Given a certain budget, finding the best nutrition has also been explored [2]. Quantitative approaches of most scoring mechanisms show weak associations with actual disease outcomes [1, 14]. Efforts in modeling expert knowledge has just used linear correlations with a small panel of nutritionists [8]. Because nutrition facts are readily available for all major restaurant chains and for packaged items, algorithms that use this information are most promising for immediate consumer use. The North American derived Nutrient Rich Foods Index 6.3 (NRF) [4], French derived SAIN/LIM method [15], and British FSA [6] all are based more heavily on available nutrition facts. Evaluation of online recipes using these previous methods have shown that users are unaware of the healthiness of the food [13]. Popular food mobile apps, like Yelp.com amongst others, allow the user to search for their restaurants in their vicinity but the user has to spend considerable effort to find a dish they prefer which satisfies their preferences. One app, named HealthyOut, allows users to filter items with certain allergens (which do not follow standard USDA guidelines) and calories caps [10]. Delivery platforms are in hot demand with systems like DeliveryHero.com amongst others attract users through convenience. Most importantly, health and allergy information is never taken into consideration most existing platforms.

3 System Architecture

Our basic architecture applies the algorithms we have developed to the meals available in a given vicinity surrounding a user. The person vector is defined by their location and the entity vector is defined based on the nutritional analysis of each dish.

The first major component includes the **data filter** to ensure quality recommendations. Data quality is checked by numeric checks on ingredients and nutritional values. The filters are: 1. **Calories** filter ensures that the caloric value provided matches the nutritional value (carbohydrates, fat and alcohol) available with the dish. 2. **Carbohydrates** filter ensures that the total carbohydrates reported matches with different sources of carbs (such as sugar, fiber and starch). 3. **Fat** filter ensures that reported total fat with the meal matches with different sources of fat (such as saturated fat, trans fat etc.). 4. **Red meat filter** ensures that if a dish contains red meat then the quantity of saturated fat reported is not zero.

The second major component **simulates the expert knowledge**. We assign a personalized health score (1–100 with 100 being healthiest) to every dish and food item based on their nutritional content and the caloric needs of the user that are located near the user. This score evaluates the items in a much more relevant manner for consumers to make their dietary choices, which has been called for previously as the Nutrient Density Score [3]. There are standardized algorithms available for measuring the nutrient density in the food items but none have been used in a user friendly manner. We are incorporating the expert knowledge of the dietitians via this algorithm and providing instant guidance around the clock to our users. We call our algorithmic scoring system Environment and Life Integreated eXpert Individualized Recommendation System (ELIXIR) (Algorithm 1), which uses expert tuned weights (Table 1). The weights were tuned with a nutrition expert manually adjusting the weights till the rank list of the items represented an accurate depiction of what the human nutritionist would suggest. The algorithm considers 3 different categories of macro nutrients: recommended base and additional nutrients, and restricted base nutrients. In simple terms, the algorithm places healthy components of the nutrition in the numerator, and unhealthy sections in the denominator. The ratio of these two components is then scaled from 1–100 for a user friendly experience.

The last component of the **user interface** involves a smart phone application for a logged in user (Fig. 3). This information is then used to show them the best available meals (based on their requirements) in the vicinity in form of a map view and a list view. The user also has the ability to search for a particular type of dish (eg. pizza) or a particular restaurant. The application would recommend the healthiest dish related to the search query in the user local vicinity.

4 Dataset

We have used two independent datasets for our experiments. First is the USDA food composition database, which is publicly available at USDA.gov. The USDA food composition database contains nutritional values for 158,552 food items and the appropriate food group. Second, we created a geo-tagged nutritional dataset for restaurant dishes. This was done by scraping the restaurant menus using Google Places API to search for restaurants in the California region. The data set contains dishes with nutrition facts from 596 food chain menus from Google.

We match the locations of restaurants to the respective dishes to create 10 million geo-tagged dish/nutrition dataset of California, USA. Figure 4 illustrates data quality after filtering. The health score for each dish was calculated using Algorithm 1. The distribution of these dishes across the ELIXIR spectrum is shown in Fig. 5. The database distribution in Fig. 5 does not contain duplicate dishes.

Algorithm 1. ELIXIR

procedure $\mathrm{ELIXIR-SCORE}(\mathrm{weights}, \mathrm{Daily\ Values}, \mathrm{Mult})$

$RecBN = (Protien, Fiber)$

$RecAN = (VitA, VitC, Ca, Fe)$

$RestBN = (Cal, Chol, Na, SatFat, TotFat, Sugar)$

$$RecBase = \sum_{i \in RecBase} weights[i] * \frac{dish[i]}{DailyValues[i]}$$

$$RecBase = RecBase + weights[Fiber] * \frac{dish[Fiber]}{dish[Carb]} + weights[ComplexCarb] * \frac{(dish[Carb] - dish[Fiber] - dish[Sugar])}{dish[Carb]}$$

$$RecAdd = \sum_{i \in RecAN} weights[i] * \frac{dish[i]}{DailyValues[i]}$$

$$RestBase = \sum_{i \in RestBN} weights[i] * \frac{dish[i]}{DailyValues[i]}$$

$$RestBase = RestBase + weights[Carb] * \frac{dish[Sugar]}{dish[Carb]} + weights[SatFat] * \frac{dish[SatFat]}{dish[TotalFat]} + weights[TransFat] * dish[TransFat]$$

$$BaseElixir = \frac{(RecBase + Mult * RecAdd)}{((1 + Mult) * (RestBase))}$$

return $BaseElixir$

end procedure

5 Experiments and Results

The recommendation problem for food is inherently more difficult than the search problem. To illustrate the scale, a 20 km radius centered in Los Angeles, CA includes 32,000 restaurants, each having nearly 70 menu items on an average. These 2.24 million menu items must be ranked to maximize person's nutritional and culinary expectations. This is beyond the capacity of human dietitians. Disregarding this problem, we explored how much variance expert dietitians would have in their recommendations. Seven clinical dietitians were given a list of 50 meals with nutrition facts and images of the dishes to rank with a score of 1–10, 1 being the most unhealthy, and 10 being very healthy. Figure 2 shows that for most dishes, there is a large range of opinions on how healthy dishes are. Even though dietitians were given the nutrition facts, the range demonstrates how human evaluators are not quantitatively precise in their recommendations. We have compared the proposed algorithm (ELIXIR) against existing nutritional ranking algorithms (FSA, SAIN, NRF) by calculating mean scores for different food groups present in the USDA dataset. The values are plotted against Energy density (calories per 100g) in Fig. 6 Given the consensus knowledge about nutrition in Fig. 1, we show in Fig. 6, we can clearly separate healthy and unhealthy items on the USDA database of 158,522 items, which other global algorithms are unable to accomplish. This is one piece of confirmation that ELIXIR algorithm can encapsulate expert knowledge. We then evaluate restaurant food items that are geo-tagged in the user system with ELIXIR When comparing the average ratings by expert dietitians for the top 50 recommendations via each global algorithm, ELIXIR has a clear advantage. ELIXIR scored an average of 8.9 out of 10, SAIN average at 8.2, FSA at 7.1, and NRF at 6.9. We use top 50 recommendations because this is primarily recommendation system, where top results are the most relevant from the user's perspective as they are unlikely to browse through all the available options.

6 Future Work

Camera Based Logging for Non-Purchased Items:

This constitutes about half of the individual's diet. Thus using the smart phone camera to capture the food items to auto-populate a health diary is essential for diet evaluation.

Adaptive weights and Daily Values:

The algorithm presented in the paper can be viewed as the inner most layer in a health based personalized food ranking system, i.e. the algorithm is to be used to provide a quantitative measure of how a given food item would affect the person's health given their context and health status. The layers above this are responsible for adjusting the weights and daily nutritional values for the person based on data such as activity and diet history with environmental factors such as temperature and altitude.

Determining portion sizes:

A meal may consist of different food items in varying portions such that the overall meal may still be healthy even if there are a few unhealthy items (e.g. chocolate cake slice for dessert). Determining ideal portion sizes is out of scope for this paper and is a topic for future research that incorporates total diet tracking and recommendations.

Knowledge Base of Taste/Cuisine:

Most people do not eat healthy food if it tastes bad. In order to enable people to make healthy lifestyle choices, we need to make sure that the recommendations are aligned with the user preferences while maintaining their health goals/status.

User Filtering System:

Filtering items at an ingredient level can help unique allergy needs. Food-drug interactions can also be captured through this method.

7 Conclusions

Our goal is to rapidly connect people to the healthy food. Expert recommendations with context increases probability of positive health actions. Traditional advertising, popularity based, or importance based rank listing systems will change with health based recommendations. Food providers are motivated to supply products that are inherently healthy to have a high rank result. The most important concept in this paper is how expert knowledge and health multimedia fusion will fuel the recommendation engines of the future.

References

1. Asghari G, Azizi F: A systematic review of diet quality indices in relation to obesity. Br. J. Nutr, 1–11 (2017)
2. Darmon N, Darmon M, Maillot M, Drewnowski A: A nutrient density standard for vegetables and fruits: nutrients per calorie and nutrients per unit cost. J. Am. Diet. Assoc 105(12), 1881–1887 (2005) [PubMed: 16321593]
3. Drewnowski A: Concept of a nutritious food: toward a nutrient density score. Am. J. Clin. Nutr 82(4), 721–32 (2005) [PubMed: 16210699]
4. Fulgoni VL, Keast DR, Drewnowski A: Development and validation of the nutrient-rich foods index: a tool to measure nutritional quality of foods. J. Nutr 139(8), 1549–1554 (2009) [PubMed: 19549759]
5. Guenther PM, Kirkpatrick SI, Reedy J, Krebs-Smith SM, Buckman DW, Dodd KW, Casavale KO, Carroll RJ: The healthy eating index-2010 is a valid and reliable measure of diet quality according to the 2010 dietary guidelines for americans. J. Nutr 144(3), 399–407 (2014) [PubMed: 24453128]
6. Julia C, Méjean C, Touvier M, Pneau S, Lassale C, Ducrot P, Hercberg S, Kesse-Guyot E: Validation of the FSA nutrient profiling system dietary index in French adults, findings from SUVIMAX study. Eur. J. Nutr 55(5), 1901–1910 (2016) [PubMed: 26293977]
7. Kennedy E: Putting the pyramid into action: the healthy eating index and food quality score. Asia Pac. J. Clin. Nutr 17(Suppl 1), 70–4 (2008) [PubMed: 18296305]
8. Martin JM, Beshears J, Milkman KL, Bazerman MH, Sutherland LA: Modeling expert opinions on food healthfulness: a nutrition metric. J. Am. Diet. Assoc 109(6), 1088–1091 (2009) [PubMed: 19465193]
9. Monsivais P, Aggarwal A, Drewnowski A: Are socio-economic disparities in diet quality explained by diet cost? J. Epidemiol. Community Health 66(6), 530–535 (2012) [PubMed: 21148819]
10. Rise Labs Inc., HealthyOut Mobile App (2015)
11. Sherifali D, Viscardi V, Bai J-W, Ali RMU: Evaluating the effect of a diabetes health coach in individuals with type 2 diabetes. Can. J. Diab 40(1), 84–94 (2016)
12. Topol EJ: The Creative Destruction of Medicine: How the Digital Revolution will Create Better Health Care. Basic Books, New York (2012)
13. Trattner C, Elsweiler D, Howard S: Estimating the healthiness of internet recipes: a cross-sectional study. Front. Pub. Health 5, 16 (2017) [PubMed: 28243587]

14. Waijers PMCM, Feskens EJM, Ocké MC: A critical review of predefined diet quality scores. Br. J. Nutr 97(2), 219–231 (2007) [PubMed: 17298689]

15. World Health Organization. Nutrient profiling: Report of a WHO/IASO technical meeting, pp. 1–18, 10 2010

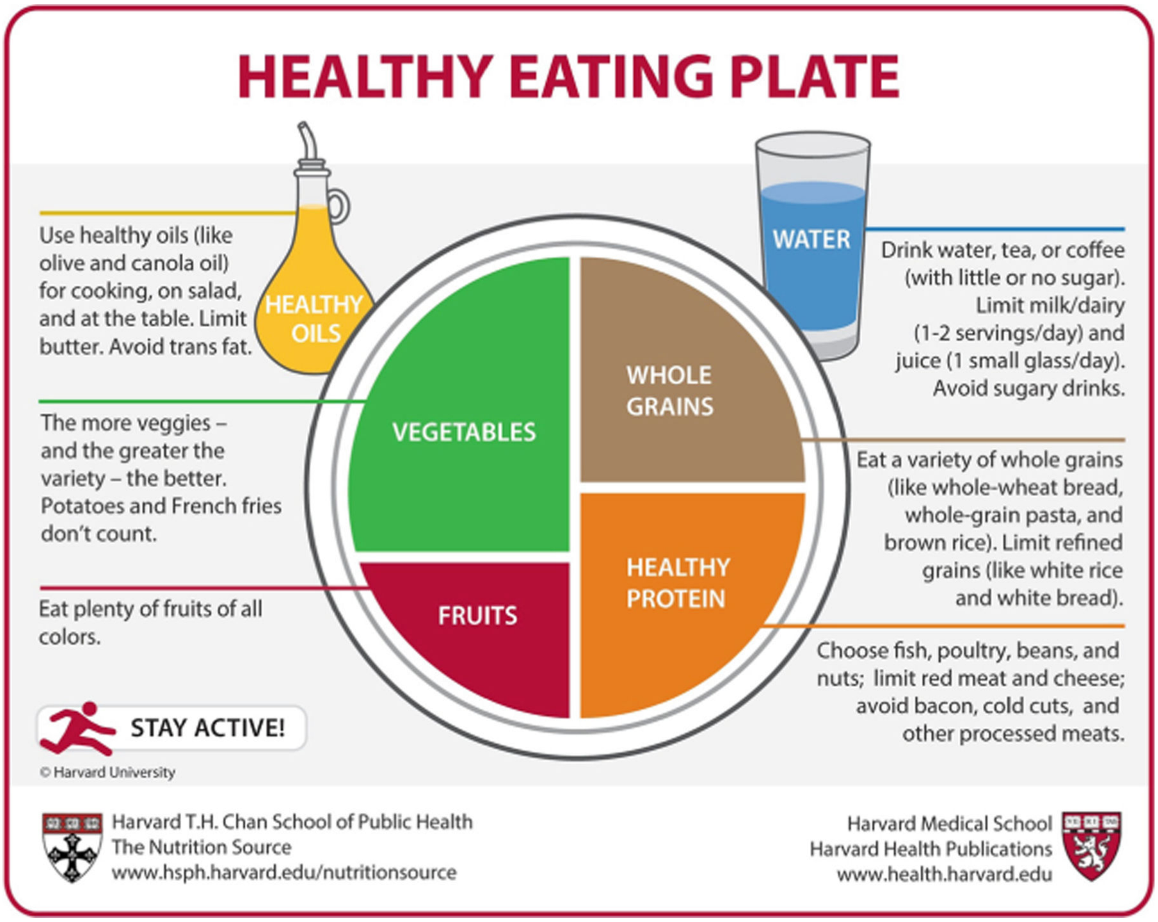

Fig. 1.

Recommendations from health experts as shown here from the Harvard Medical School are compiled from consensus nutrition experts. Yet these recommendations are hard to translate into everyday life decisions for the public population, especially in the context of eating out.

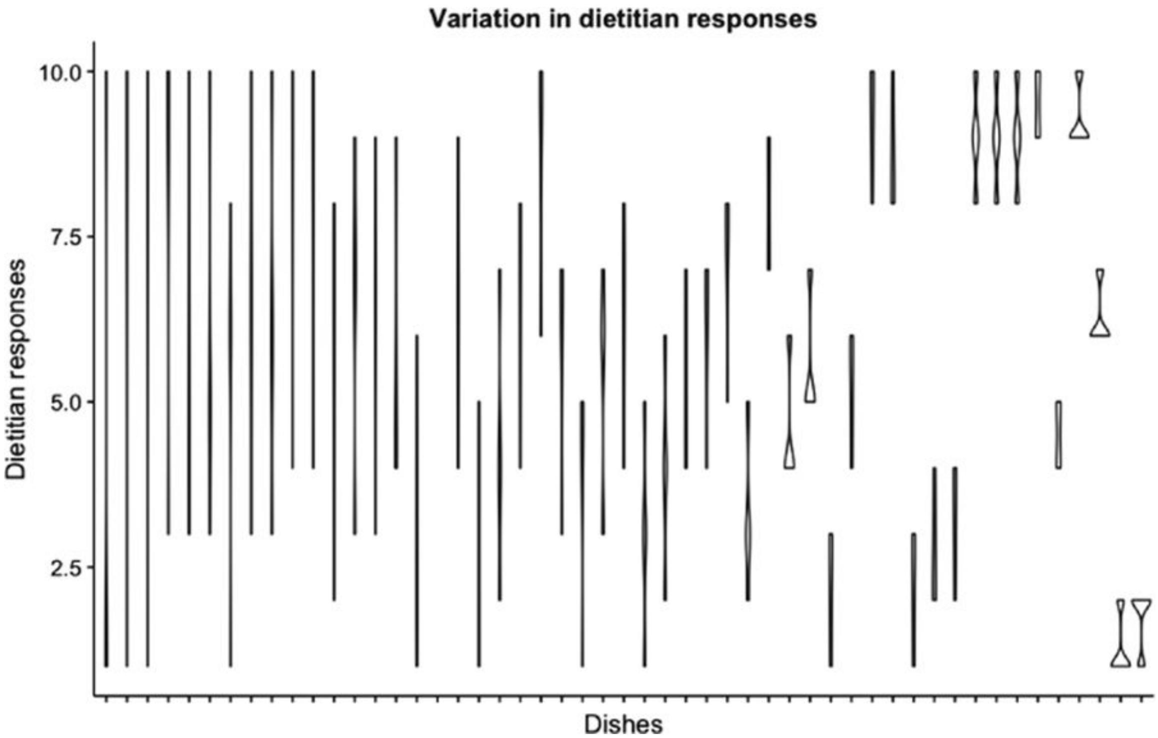

Fig. 2.

For 50 dishes given on the x-axis, each dish was given a score of 1–10, 1 being the most unhealthy, and 10 being very healthy. Amongst 7 professional dietitians, the variance for a given dish was highly unpredictable, with only 19 items having less than a 30% range.

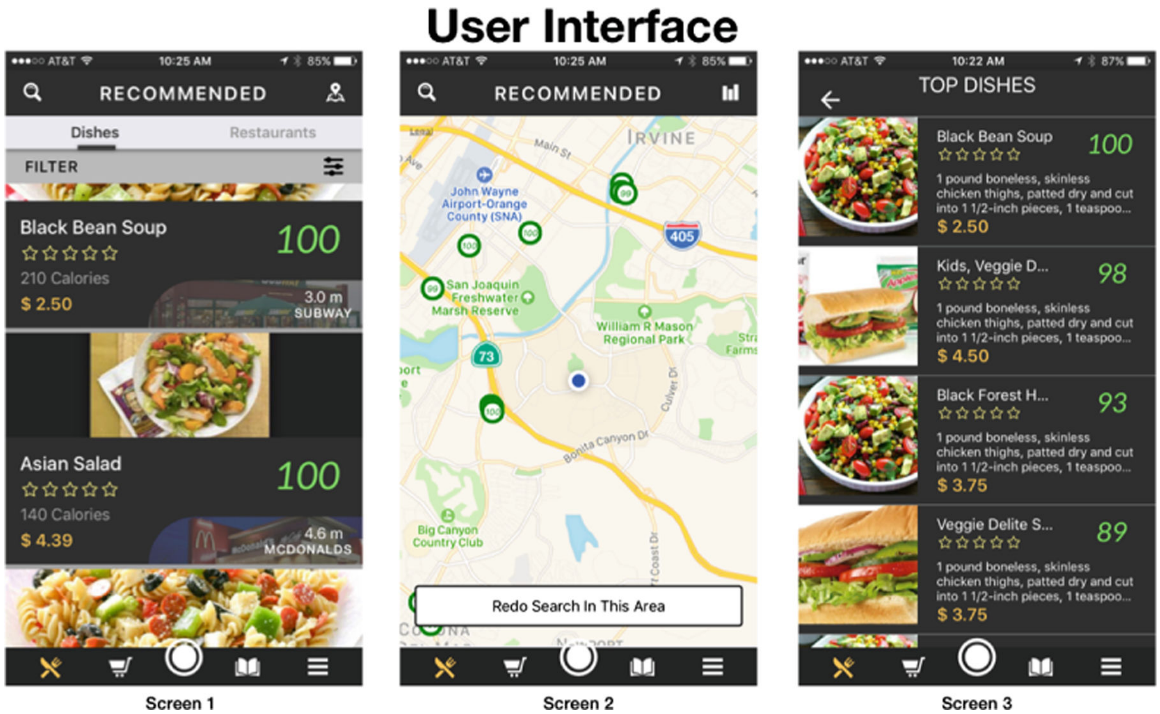

Fig. 3.

User interface demonstration through mobile application. Screen 1 demonstrates how the healthiest dishes are automatically populated. S2 shows the map context of the user with locations of all the healthy dishes. S3 curates the healthiest dishes at the restaurant.

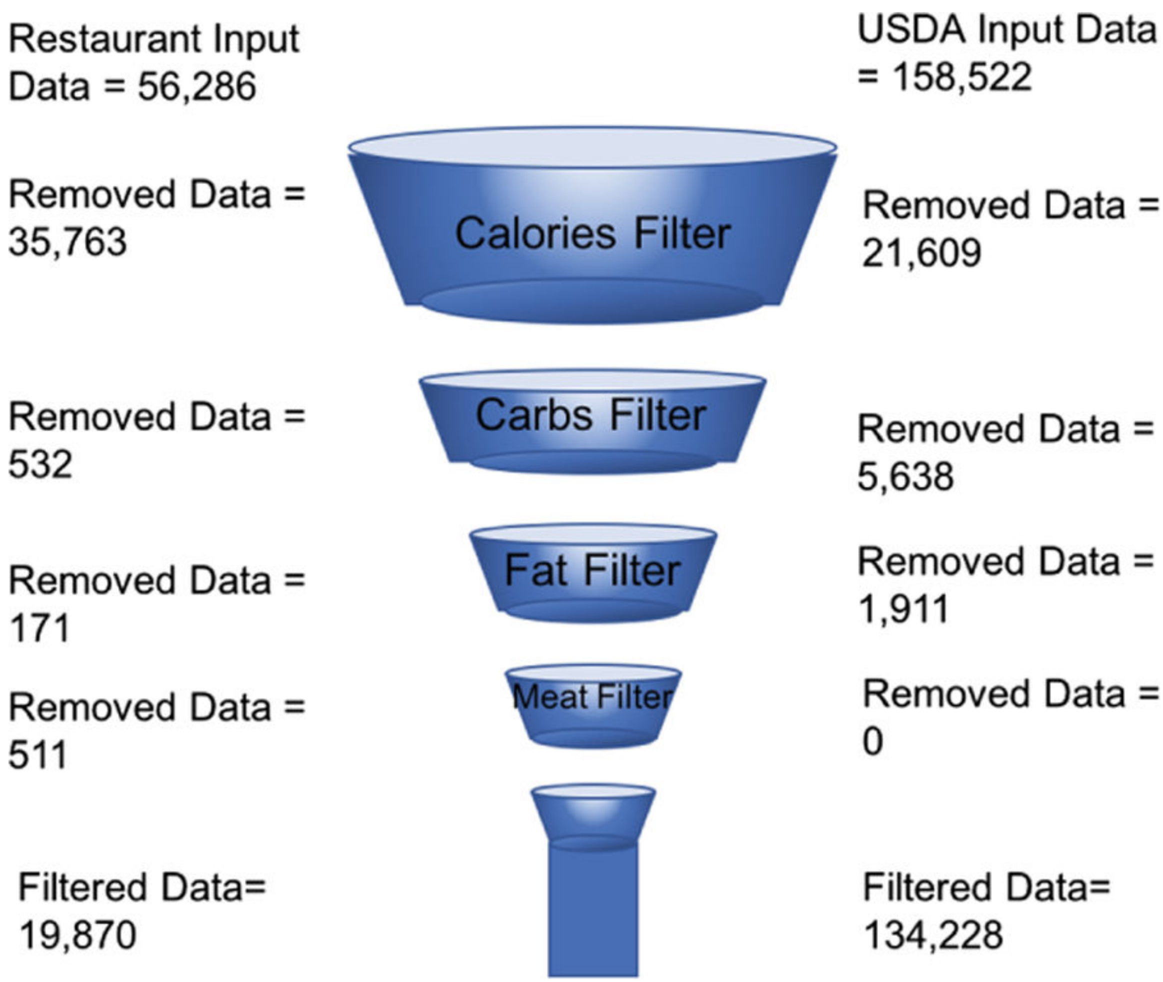

Fig. 4.
Data of menu and dish items filtered for high quality.

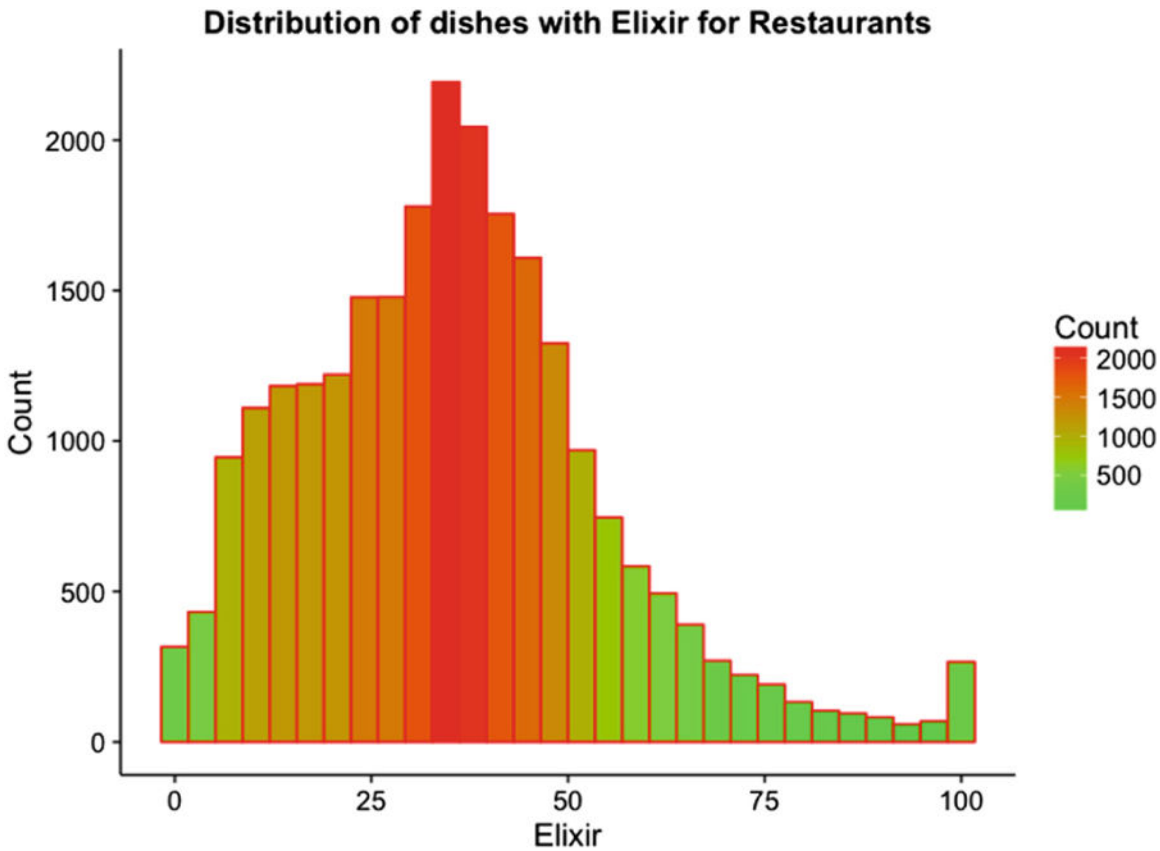

Fig. 5.
Dish database histogram along their ELIXIR scores.

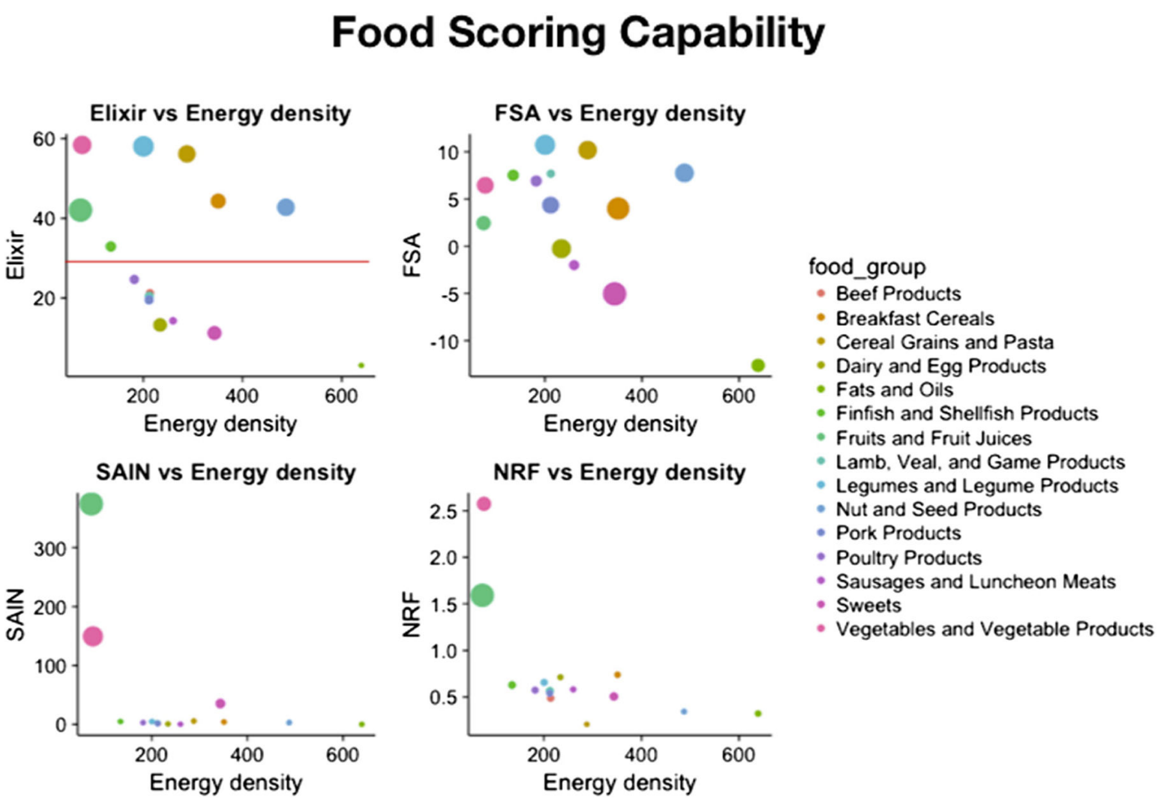

Fig. 6.

The ELIXIR algorithm is able to clearly separate the healthy food groups from the unhealthy items, as shown with the red line (at approximately an ELIXIR score of 30). Healthy food groups are defined by guidelines from Fig. 1 and the American Heart and American Diabetes Associations. This clear separation of healthy food groups from unhealthy food groups is not possible with current scoring algorithms that use nutrition facts. Energy Density is given as calories per 100 grams of food. The y-axis is the arbitrary ranking score for each algorithm. Circle size represents variance within food group.

Table 1.

Weights and Daily Values

Nutrients	Weight	Daily value
Calories	1.00	2000 cal
Protein	1.00	50 g
Sugar	1.10	50 g
Total Fat	1.10	60 g
Saturated Fat	1.70	20 g
Carbohydrate	1.00	300 g
Fiber	1.50	25 g
Sodium	1.00	2400 mg
Cholesterol	1.20	300 mg
Vit A	1.00	5000 IU
Vit C	1.00	60 mg
Calcium	1.00	1000 mg
Iron	1.00	18 mg
Trans Fat	0.91	NA
Complex Carb	0.10	NA