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Narrative review: Food image use for machine learnings' function in dietary assessment and real time nutrition feedback and education

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Narrative Review: Food Image Use for Machine Learnings' Function in Dietary Assessment and Real Time Nutrition Feedback and Education

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Table of Contents

Dedication / Acknowledgements

This manuscript is dedicated to surviving car accidents, mental health struggles, global pandemics, dietetic internships, and Hurricane Ian.

I would like to thank my advisor Laura Dengo, PhD, for her patience throughout this research process. I would also like to thank my committee members Michelle Hesse, PhD, and Danielle Torisky, PhD, for their support. Special thanks to the JMU Dietetics quantity class of 2021 for allowing me to use their Dietetics food labs for data and image collection.

List of Tables

List of Figures / Images

Abstract

Technology has played a key role in advancing the health and agriculture sectors to improve obesity rates, disease control, food waste, and overall health disparities. However, these health and lifestyle determinants continue to plague the United States population. While new technologies have been and are currently being developed to address these concerns, they may not be practical for the general population. Utilizing machine learning advancement in food recognition using smartphone technology may be a means to improve the dietary component of nutrition assessments while providing valuable nutrition feedback. This narrative review was conducted to assess the current state of the literature on nutrition technology using image recognition for practical applications, while also proposing theoretical uses for the technology to improve quality of life through dietary feedback.

Part 1: Original project **“**Machine Learning Using a Food Image Database to Provide Real Time Dietary Intake Feedback and Nutrition Education**”**

1.A. Research Question / Objectives

Research Question

How to develop the framework for a real time dietary feedback technology?

Hypothesis

The prototype will be able to integrate the publicly available food image databases and the JMU-EMU developed database to accurately recognize foods and provide real-time feedback to promote healthy dietary practices.

Objectives

1. Explore available public food image databases for appropriateness for machine learning.
2. To create a metadata database of standardized food images to teach the prototype, in collaboration with EMU computer science, how to accurately recognize food types and amounts.
3. To develop priority nutrition education messages to be delivered via human-machine interaction to combat food waste and improve dietary choices.

1.B. Methods for Capturing Images to Build a Dataset for Machine Training.

Food Image Capturing Technology and Tools

A standardized procedure for image collection and data entry was created to develop our unique dataset for machine training and learning. Nasco food models[1] and real food were used to develop an image dataset with the image identification number, foods name, corresponding weight, and volume measurements being input for metadata to aid in food recognition and volume estimations. Images were collected on an 8-inch white plate, with food volumes being measured on the “Rubbermaid 1812595 Pelouze 12 lb. Premium Stainless Steel Digital Portion Control Scale”. A standard LED ring light was used to provide consistent lighting of the plates to decrease the chance of noise in the image. All images were taken on an iPhone 12 Pro at 4.2mm f/1.6. Excel was utilized for image labeling to place truth values on food names, weights, colors, state of processing, and cooking/preparation methods.

Image 1A. Setup and process of collecting images for data collection for developing an image database for machine learning.

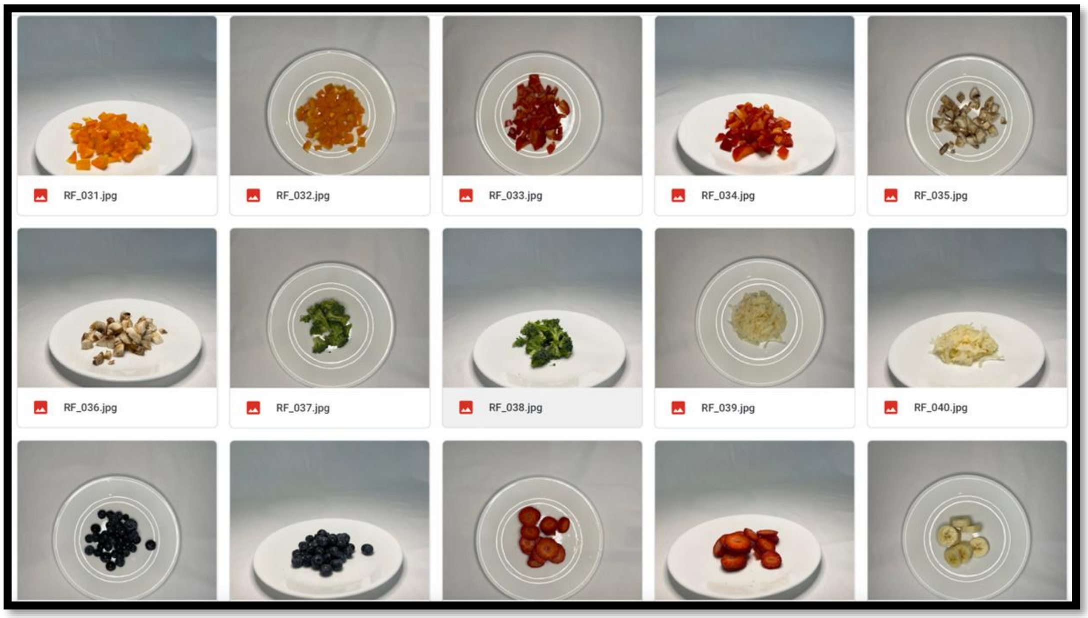

Image 2A. Library of image collection database using a frontal/aerial view of images for volume estimation enhancement during the machine learning process.

Food Image Metadata .XLSX

Last edit was on November 7, 2020

Image Number	Food name	Type	Color	Preparation Method	State (Raw, Baked, Fried, Boiled)	Weight (grams)	Volume (milliliters)
RF_001	Ripe Mango (large)	Fruit	Yellow	Whole	Raw	371	Whole Fruit
RF_002	Banana	Fruit	Yellow	Whole	Raw	200	Whole Fruit
RF_003	Passion Fruit (3)	Fruit	Green	Whole	Raw	158	Whole Fruit
RF_004	Passion Fruit	Fruit	Green	Whole	Raw	53	Whole Fruit
RF_005	Unripe Mango (small)	Fruit	Yellow	Whole	Raw	234	Whole Fruit
RF_006	Dragon Fruit	Fruit	White	Whole	Raw	288	Whole Fruit
RF_007	Tomato	Fruit	Red	Whole	Raw	205	Whole Fruit
RF_008	Red Bell Pepper	Fruit	Red	Whole	Raw	220	Whole Fruit
RF_009	Green Bell Pepper	Fruit	Green	Whole	Raw	213	Whole Fruit
RF_010	Cantaloupe	Fruit	Orange	Whole	Raw	1331	Whole Fruit
RF_011	Cucumber	Vegetable	Green	Whole	Raw	193	Whole Fruit
RF_012	Lime	Fruit	Green	Whole	Raw	113	Whole Fruit
RF_013	Lemon	Fruit	Yellow	Whole	Raw	117	Whole Fruit
RF_014	Watermelon	Fruit	Pink	Whole	Raw	4441	Whole Fruit
RF_015	Pineapple	Fruit	Yellow	Whole	Raw	1774	Whole Fruit
RF_016	Cucumber	Fruit	Green	Diced	Raw	75	118
RF_017	Green Bell Pepper	Fruit	Green	Diced	Raw	74	118
RF_018	Red Bell Pepper	Fruit	Red	Diced	Raw	80	118
RF_019	Carrot	Vegetable	Orange	Diced	Raw	73	118
RF_020	Lime	Fruit	Green	Wedges	Raw	82	118
RF_021	Onion	Vegetables	White	Diced	Raw	70	118
RF_022	Watermelon	Fruit	Pink	Diced	Raw	91	118
RF_023	Carrot	Vegetable	Orange	Whole	Raw	64	118
RF_024	Tomato	Fruit	Tomato	Whole	Raw	77	118
RF_025	Strawberries	Fruit	Red	Whole	Raw	67	118
RF_026	Passion Fruit	Fruit	Green	Halved	Raw	55	118
RF_027	Green Apple	Fruit	Green	Sliced	Raw	92	118
RF_028	Mango	Fruit	Yellow	Cubed	Raw	115	118
RF_029	Pineapple	Fruit	Yellow	Diced	Raw	88	118

Figure 1A. The food image database developed to contain metadata of images collected during the research process for training machine learning device.

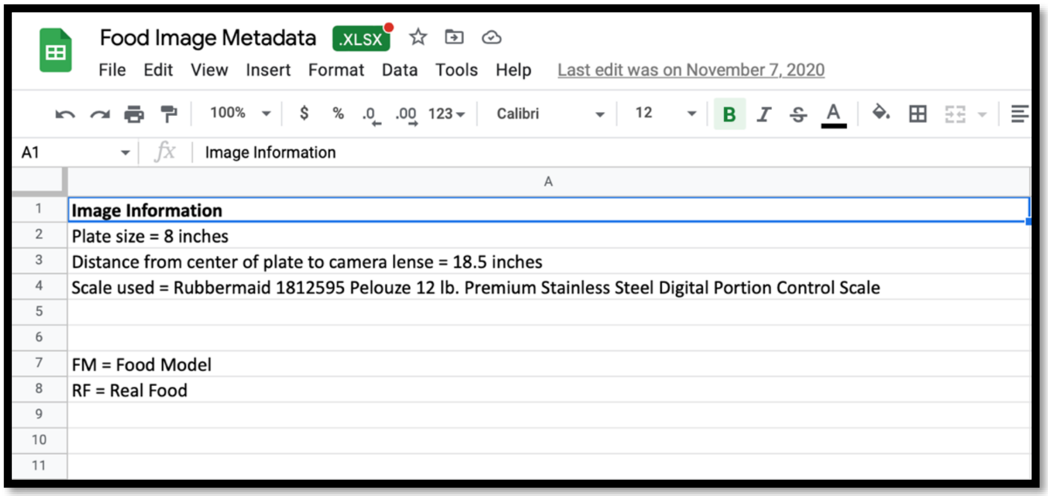

Figure 2A. Standardization information for the setup of data collection.

The system would also use current existing systems as shown in Table 1.A/B, to provide a more robust catalog of images to train on, in hopes of improving food recognition accuracy. The process for searching for the listed databases consisted of searching PubMed, Google Scholar, and Scopus for research articles that included food images for machine learning. A definitive search criterion was not established as that was not the aim of this thesis.

Table 1B. Summary of current food image databases used for machine learning training and dataset size.

Database, Year Published	City, Country: Setting	Validation:	Metadata Available, Standardized (Y/N)	Image Quality (High/Low)	Dataset Size
FRIDa[2] 2013	Trieste, Italy: International School for Advanced Studies	Validated on standard variables, perceived calorie content, and visual features	Yes No	Low	900 images
Food-Pics[3] 2014	Salzburg, Austria: University of Salzburg	Cross-validated with mean agreement of r= 0.95	Yes No	Low	896 images
OLAF[4] 2014	Granada, Spain: University of Granada	Not Disclosed	No No	High	96 images
EPFL[5] 2015	Lausanne, Switzerland: Swiss Federal Institute of Technology	Not Disclosed	No No	Low	16,643 images

CROCUFID[6] 2018	Wageningen, Netherlands: Kikkoman Europe R&D Laboratory	Additional validation needed	Yes Yes	High	675 images
F4H[7] 2015	Utrecht, Netherlands: Image Science Institute, University Medical Center Utrecht	Not Disclosed	Yes Yes	High	377 images
PFID[8] 2009	Pittsburg, Pennsylvania: Intel Labs Pittsburgh	Three-fold cross validation	No No	High	4,545 images
NU Food 360x10[9] 2017	Nagoya, Japan: Nagoya University	Not Disclosed	No No	Low	360 images
ChineseFoodNet[10] 2017	San Jose, CA Shenzhen, Guangdong, China: Midea Research Institute	Unspecified	No No	Unknown	185,628 images

UNICT[11] 2014	Catania, Italy: University of Catania	Not Disclosed	No No	Low	899 images
UEC Food 100[12] 2012	Chofu-shi, Tokyo, Japan: The University of Electro-Communications	5-fold cross validation	No No	Low	13,125 images
UEC Food 256[12] 2014	Chofu-shi, Tokyo, Japan: The University of Electro-Communications	Cross-validation using Support Vector Machines	No No	Low	31,907 images
UEC-Foodpix Complete[12] 2021	Chofu-shi, Tokyo, Japan: The University of Electro-Communications	Not disclosed	No No	Low	10,000 images
School Lunch Data[12] 2017	Chofu-shi, Tokyo, Japan: The University of Electro-Communications	Not Disclosed	No No	Low	3,940 images

VIREO-172[13] 2016	Kowloon, Hong Kong: City University of Hong Kong	5-fold cross validation	No No	Low	110,241 images
UNIMIB2015[14] 2015	Milano, Italy: University of Milano-Bicocca	Cross-validation process	Yes No	High	2,000 images
UNIMIB2016[14] 2016	Milano, Italy: University of Milano-Bicocca	Cross-validation process	Yes No	High	1,027 images
Food-101[15] 2014	Zurich, Switzerland: ETH Computer Vision Labs	Unspecified	No No	Low	101,000 images
Food-475[16] 2018	Milano, Italy: University of Milano-Bicocca	Unspecified	No No	Low	247,636 images

Additional steps:

Due to Covid-19 and various obstacles in the collaboration with Eastern Mennonite University (EMU) this original project was unable to proceed beyond the preliminary work conducted during the data collection phase. If the project were to have continued, these additional steps would have followed in the development of this thesis.

- The databases found would be integrated/merged with the database created for this project.
    - The database built in the preliminary work would be expanded on.
- A food image standardization process would be developed that could be followed into the future for homogeneity.
    - Metadata formatting and image inputs would be described and transformed for the machine learning process.
    - Nutrition education outputs for prompts to improve dietary quality would be developed to provide user feedback.
- The process of the involvement of Aramark and other food vendors for food analysis would have been discussed.
- Algorithm and machine learning descriptions would be provided by EMU.
- EMU would conduct the metadata, food image collection, transference process and the statistical analysis to assess the validity and reliability of the data being captured.

Part 2: Narrative Review "Food Image Use for Machine Learnings' Function in Dietary Assessment and Real Time Nutrition Feedback and Education"

2.A. Research Question and Objectives

Research Question

What is the current state of literature around nutrition technology using image recognition for practical applications, and what theoretical uses for the technology can be implemented to improve quality of life through dietary feedback?

Objectives

1. Review the current applications of nutrition technology where health outcomes and food waste are measured, providing understanding of the development and function of food recognition and volume estimation using machine learning.

2. Examine ways nutrition technology can be implemented to improve health outcomes or limit food waste in a clinical or community setting while proposing how new technology can be used for future research and applications.

3. Propose how technology can be used to promote health through improved dietary assessments, nutrition education/feedback, and its potential to improve health equity through its utilization.

2.B. Manuscript:

Abstract

Technology has played a key role in advancing the health and agriculture sectors to improve obesity rates, disease control, food waste, and overall health disparities. However, these health and lifestyle determinants continue to plague the United States population. While new technologies have been and are currently being developed to address these concerns, they may not be practical for the general population. Utilizing machine learning advancement in food recognition using smartphone technology may be a means to improve the dietary component of nutrition assessments while providing valuable nutrition feedback. This narrative review was conducted to assess the current state of the literature on nutrition technology using image recognition for practical applications, while also proposing theoretical uses for the technology to improve quality of life through dietary feedback.

Keywords: *Nutrition technology, Food image recognition, Nutrition feedback technology, Nutrition education feedback, Nutrition technology applications, Machine learning*

Introduction

Since the inception of the machine learning model presented by Donald Hebb[17], the theory has turned from simple processes, like IBM's artificial intelligence (AI) checker program[18], to more complex utilization with image recognition in self-driving vehicles[19]. Machine learning, in its simplest terms, is the use of data and algorithms to teach a computer system to learn as a human would to fulfill a task successfully[20]. There has been a steep incline in the development and utilization of AI and machine learning technology over the past decade[21]. Technology has played a key role in advancing health and agriculture fields with the intention of improving obesity, disease management, food waste, and general health disparities; however, determinants of these health conditions and lifestyle behaviors continue to plague the United States (U.S.) population[22,23]. Obesity has reached a new high among U.S. citizens at 42.4% in adults and 19.3% in youth[24]. Chronic disease accounts for $3.8 trillion per year, with 6 in 10 adults having a chronic illness and 4 in 10 having two or more[25]. The health disparities among black, indigenous, and people of color are disproportionate compared to white U.S. citizens regarding mortality, mental health, chronic health issues, and health care coverage[26]. Compounding on the aforementioned issues, food waste per year among U.S. citizens is between 30-40% of the food supply, weighing in at 80 billion pounds of food waste and costing $218 billion per year[27]. These problems weigh heavily on both the individual and institutions that serve to support the community’s health at large. Food and nutrition play a crucial role in the etiology of these issues and should be a critical component of interventions set to ameliorate these problems.

Nutrition assessment is the first step in the nutrition care process, establishing an appropriate diagnosis, intervention, and evaluation are all based on information obtained during the assessment process[28]. For this reason, the accuracy of information obtained during the assessment is crucial in providing appropriate steps in care, as interventions are a cascade of actions based on information obtained during assessment[29]. Some of the most common forms of dietary assessment, a component of nutrition assessment, are food frequency questionnaires (FFQ), 24-hour dietary recalls, and 3-day food diaries (3DFD). While they have their uses in the assessment process, they are not without limitations which include: participant burden, bias, cultural appropriateness, impacted by cognitive capabilities, do not provide dietary feedback or education, may not assess energy intake accurately, and may not be an accurate depiction of normal dietary intake[30]. Many of these limitations may be overcome by utilizing readily available tools or applications that individuals have access to through their mobile devices[31–38].

While there are many new technological tools aimed to address the above-mentioned concerns, many can be expensive, invasive, or impractical outside of the research setting, some examples include: glucose monitoring contact lenses, wireless glucose monitoring mouthguard devices, and wearable tattoos for sweat alcohol analysis[39]. The most useful tool for someone is the one that is accessible and familiar, which gives smartphone and new machine learning technologies an opportunity to make a large impact at minimal cost or burden.

Machine learning in dietary assessment can broadly be defined as the utilization of large data sets of nutrition information to teach computers to automate tasks around individuals' dietary habits without the need for explicit supervision from a human[40]. In an editorial piece (2021), Mikkelsen[41] brings to light the future of nutrition technology utilizing food image recognition and machine learning in both the research and consumer setting, examining the research of mobile nutrition assessment applications and clinical dietary intake tools for patients. Wearable technology based on machine learning and volume estimation of food[42–44], as well as hospital dietary intake monitoring systems (DIMS)[45] have been developed for research purposes, which will be discussed later in this paper. With the growth in technology and the challenges surrounding limited education on nutrition topics and/or nutrition misinformation in the general population, having a real time dietary feedback application to output nutrition information in a fast and succinct fashion could help improve everyday nutrition choices and ultimately have a positive impact on nutrition and health status.

This narrative review was conducted to assess the current state of the literature on nutrition technology using image recognition for practical applications, while also proposing theoretical uses for the technology to improve quality of life through dietary feedback. The specific objectives of this review were to:

- Review the current applications of nutrition technology where health outcomes and food waste are measured, providing understanding of the development and function of food recognition and volume estimation using machine learning.
- Examine ways nutrition technology can be implemented to improve health outcomes or limit food waste in a clinical or community setting while proposing how new technology can be used for future research and applications.

- Propose how technology can be used to promote health through improved dietary assessments, nutrition education/feedback, and its potential to improve health equity through its utilization.

Methods

From April 2021 to September 2022 SCOPUS and PUBMED were used to search for real world applications using machine learning's food recognition and volume estimation capabilities. The keywords that were used to search the literature were: 'food recognition', 'food recognition AND volume', 'food recognition AND volume estimation', 'neural network food recognition', and 'image recognition AND food application'. Article inclusion criteria consisted of publications between 2000-2022, full-text articles, peer-reviewed, original experimental studies, implementation of machine learning, English, and outcomes of using machine learning technology. Articles were excluded if they did not provide a prototype application of the food recognition technology, were theoretical in nature, a meta-analysis, or a systematic review.

The database search using keywords resulted in 642 total articles across the two platforms. After filtering the results based on inclusion criteria, the total number of articles was reduced to 250 articles which were then evaluated based on title and abstract with 10 articles meeting the inclusion criteria and 3 being added from a manual search on PubMed based on articles found during the original preliminary work, for a total of 13 articles. The summary of the literature search can be seen in Figure 1B.

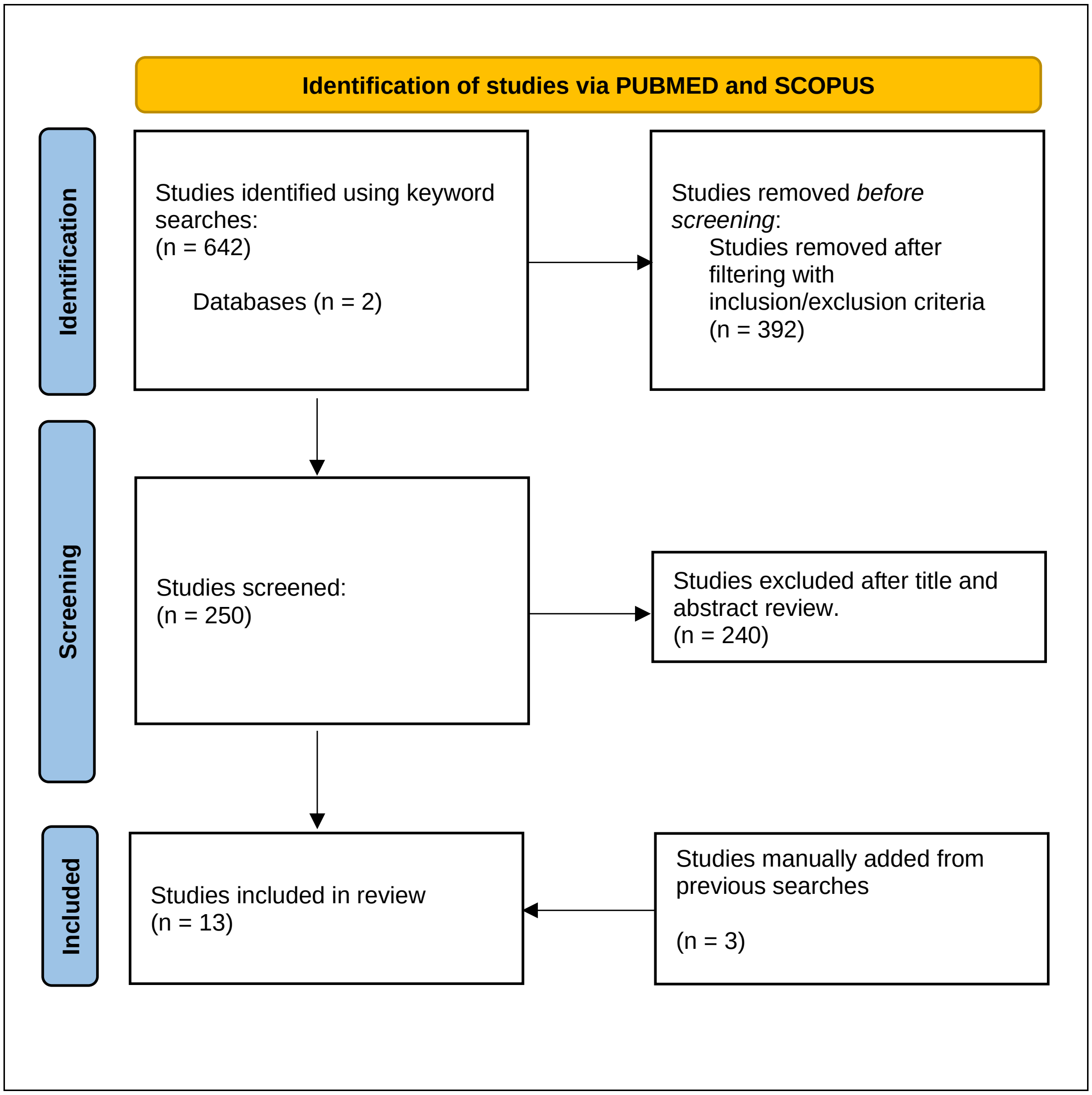

Figure 1B. Summary of article identification and exclusion process.

Discussion

Technology in Nutrition

The use of nutrition technologies to assess and track dietary intake is growing amongst everyday consumers and Registered Dietitian Nutritionists (RDNs), with many finding the burden on participants eased while also finding data agreement with the traditional methods[31]. The primary nutrition interventions found outside of the critical care setting are nutrition counseling and education. Previous work investigating nutrition education efficacy has revealed that personalized feedback and consistent long-term interventions effectively improve dietary intake of fruits and vegetables with sustained change[46–48]. Just as with technology for dietary assessment, there is a growing body of evidence that RDNs and patients may benefit from a more robust catalog of mobile education-based applications for improving health in those suffering from chronic illnesses, obesity, or wanting to make lifestyle changes[31–38].

As of 2021, 85% of adult U.S. citizens own a smartphone[49] which increases the population's ability to access health, nutrition, and food information. There are currently 325,000+ mobile health apps available for smartphone users, with a large number focused on nutrition tracking[50]; however, it is unknown whether individuals are improving their nutrition and food consumption practices as a result of utilizing the available technology to them. The current statistics on obesity, chronic disease prevalence, and food waste would suggest a disconnect with access to the information for effectively using educational resources and lifestyle changes. This access to technology and a library of health applications allows a bridge across all demographics to help reduce health disparities and improve health equity. There is a way to level the proverbial playing field of inequity we face by having free resources that can overcome the current barriers that plague those of culturally diverse backgrounds or in low socioeconomic status while targeting their specific needs.

Outside of the use of smartphone applications for dietary tracking and nutrition information, there is a growing body of wearable nutrition technologies being used and researched to measure precise nutrient intake. Technology has been developed using electrodes for glucose detection, electrochemical tags for heavy metal detection, microfluidic biosensors for microbial detection, glucose monitoring smartwatches, wireless epidermal patches for sweat detection, wireless patches and sweatbands for sweat mineral detection, contact lenses for glucose monitoring, and wireless tooth mounted, radiofrequency sensors to monitor drinking[39]. While innovative, the cost and practical application of these technologies may not be reasonable for the general population; especially since many of these technologies still need the use of the smartphone as an interface to see data[39]. This may not be feasible for those in a low socioeconomic standing, as it would require the additional cost of a specialized technology along with the cost of a smartphone. For these reasons, it may be best to focus on the improvement of mobile nutrition technologies that utilize machine learning, as they can be readily available through smartphone devices the population already owns. These technological applications can be designed in a way that is easy to navigate, provides dietary feedback, and is curated to the learning level of the individual to allow for opportunities for education.

Current Applications of Food Recognition for Dietary Feedback and Assessment Using Machine Learning

When reviewing the literature for studies that utilize food recognition technology, two primary domains emerged where research was being conducted: the hospital and outpatient settings. Two additional domains that had limited research on the application of food image recognition were in the smart home and commercial food service settings. The overall purpose, setting, and results of those studies can be seen in Table 2.B (p. 48).

Hospital Setting

In the clinical setting, malnutrition is a critical component in disease states, mortality, and cost of care, with roughly 70% of inpatient adults experiencing malnutrition.[51] Dietary assessment in the clinical setting plays a crucial role in understanding patient needs and providing interventions to improve outcomes, including length of stays, readmissions, morbidity, and overall mortality all of which economically impact the healthcare system significantly [52,53,54]. The current method for assessing food intake is performed manually and is often plagued with wide variations between recorders and overestimating consumption[55]; which, in a nutritionally at-risk population can be harmful and have a significant impact on recovery. When addressing pathological factors, namely, infection, trauma, medical illness, malignancies, surgery, genetics, and medications it is vital to properly assess and monitor nutrient intake to ensure needs are being met to prevent patients from deterioration and need of nutrition support[56,57]. Applications of dietary intake assessment technology are starting to emerge and may help to identify those patients at risk of being malnourished and trigger interventions and assess the food waste that occurs in the hospital setting.

A hospital-based nutrition assessment prototype, known as the Dietary Intake Monitoring System (DIMS), was developed in 2014 by a team of researchers from the Research Group for Meal Science & Nutrition Science in Denmark; it utilizes a digital camera, weighing scale, infrared thermometer, radio-frequency identification (RFID) reader, and a user RFID transponder card collecting pre- and post-meal information that can be utilized for measuring food waste and patients that may be at risk of malnutrition in a gastroenterology medical and surgical ward[45]. When implemented in the medical and surgical wards, researchers found that there was statistically significant food waste in relation to portion size served to patients, with the greatest being in those who were at a nutritional risk[45,58]. Most recently, in 2018, DIMS 2.0 was validated against the weighing food method and was found to have a significant correlation with it for calculating energy ($P<0.01$) and protein ($P<0.01$) while having high inter-assessor reliability between trained and untrained individuals[59]. The first iteration of the DIMS prototype was not mobile and required trays to be brought to the device for reading; however, the latest version was built with a mobile suitcase design to allow for mobile assessment[45,59]. The system can obtain a high level of accuracy in after-meal assessments due to its ability to segment and separate out foods that have been mixed together after eating; however, researchers do note this all relies on the food being recognized and properly labeled in the system.

Similar to DIMS, Lu et al. (2021) at The University of Bern, Switzerland developed a system that is much more compact and only utilizes a depth camera for estimating portion size, food segmentation, and food recognition[60]. They achieved an estimate of nutrient intake that was 91% of the true value (actual nutrient intake) with an absolute error of 20%[60]. While the device did achieve accurate measures for food estimation compared to the actual nutrient content consumed, the study did not mention how it was utilized in the workflow of the health care team, what patient population it was tested on, and if this system is planned to be used at other hospital facilities. The authors did note that the software developed could easily be transferred over into a smartphone equipped with a depth sensor[60], making this an easy and practical tool to utilize given smartphones are regularly used during the care process.

Both systems show the efficacy of nutrition technology in the hospital setting, especially as it can capture dietary information for all patients' pre- and post-meal trays. Neither research group has put forward ideas for future research or the next steps beyond DIMS 2.0 working towards a fully automated system. These systems are both being piloted currently and are not being used regularly for nutrition interventions or nutrition education purposes.

While the present studies have focused on the accuracy of nutrient intake captured using these technologies, many other factors are worth exploring in the future for research in the hospital setting. Neither of these research groups mentioned the benefit of using this technology's image recognition to help in identifying and preventing food allergens from being served to patients. The present studies are limited to the hospitals or wards they have been tested in and have not been set in place as a standard dietary assessment protocol at these facilities. It may be beneficial to study the benefits of using a system in a long-term care facility, as up to 50% of residents are malnourished or at risk of becoming malnourished[61]. Because the assessment and monitoring process is crucial in the delivery of adequate nutrition care, comparative prospective studies on the difference in malnutrition diagnosis before and after implementation of these systems would be valuable data to assess the effectiveness of the system. While dietary assessment is only one part of the diagnosis of malnutrition, it may give greater insight into the prevalence of those not meeting their nutritional needs during hospital stays compared to traditional assessment methods. It may benefit the DIMS 2.0 research group to work with those involved in the Lu et al. group in combining their technology as they both have unique aspects. Finally, future work could be done to assess the time saved by the automation using these monitoring systems compared to the traditional method which doctors, nurses, and other healthcare workers often describe as time-consuming[62,63].

Outpatient Setting: Mobile Phone Applications

While mobile nutrition tracking applications are nothing new, there is limited use of food recognition and machine learning being implemented in this setting. There is little validated research that explores the uses of food recognition and machine learning in the mobile nutrition application industry currently. During the literature review process only four applications were found implementing this technology: GoCarb, iSpy, goFood, and Keenoa[64–70]; these studies can be seen in Table 2.B (p. 48). The primary focus of these applications has been focused on aiding in the disease management of Type 1 Diabetes or as an alternative to food records.

GoCarb was the first of these mobile applications to be researched (2016) by a group of computer scientists and medical doctors in Bern Switzerland, for the purpose of estimating the carbohydrate intake of users living with Type 1 Diabetes[69]. Researchers asked 19 volunteers, with Type 1 Diabetes, to first estimate the carbohydrate content of six meals and then use the application to capture images of food using a reference card in the shot to compare results with the true values calculated using weighted scales and the United States Department of Agriculture (USDA) nutrient database[69]. While using GoCARB, the carbohydrate estimation absolute error was 12.28 grams/meal of compared to 27.89 grams of carbohydrates when individuals estimated the carbohydrate content without using the application. GoCARB was able to successfully segment food 75.4% of the time and recognize individual food items 85.1% of the time[69]. Individuals with Type 1 Diabetes have experience when it comes to carbohydrate counting estimation, given the application outperformed a group that has experience, it may have increased benefit for groups that are not accustomed to estimating carbohydrates or portion sizes.

A later prospective, randomized controlled crossover pilot study of GoCARB by Bally et al (2017), at Bern University Hospital, evaluated the application's effectiveness on overall glucose control using sensor-augmented insulin pump therapy[65]. While it was a pilot study with a small sample size of 20 participants, GoCARB use showed a significant reduction in time spent hyperglycemic (P=0.039)[65]. Most recently, in 2018, a comparative study of GoCARB was conducted at Bern University Hospital to investigate the accuracy of the application versus six experienced RDNs, against ground truth information from weighing and calculating food composition using the USDA database[66]. The researchers saw similar accuracy in the estimation of carbohydrate content of meals compared to RDNs with the mean absolute error being 14.8g vs 14.9g[66]. Researchers have noted the limitations around the application regarding its difficulty estimating with mixed dishes or where foods overlap, limited food database to learn from, and it is only able to assess carbohydrates and not other macronutrients[66], despite researchers having suggested expanding the application's ability to also include other micro- and macronutrients for recognition to better serve a broader population[69]. In 2020, the research group at the University of Bern developed a follow-up to GoCarb called goFood with improvements in food recognition accuracy, volume estimation, and complete macronutrient estimation of protein, fat, carbohydrates, and overall calories[64]. A comparative study was performed between the goFood application and two RDNs from the United States, each with over 5 years of experience in macronutrient counting[64]. The researchers used two databases, the MADiMa database and the Fast Food database; MADiMa consisted of non-standardized meals, while the Fast Food database meals were standardized[64]. The RDNs and application used the food images to estimate the calorie and macronutrient content of meals, which were then compared to the known values[64]. The goFood application was found to have comparable nutrient estimation to RDNs on the Fast Food database and outperformed RDNs on the MADiMa database[64]. It should be taken into consideration that the MADiMa database the RDNs evaluated were of European meals; unfamiliarity may be one of the reasons for the discrepancy in estimation. The study may have benefited from a larger pool of RDNs, with the inclusion of European RDNs, to be able to compare the application to see the generalizability across various cultures. Currently, neither the GoCarb nor goFood applications are available for public use, with the goFood application currently only made for Android smartphones and research use.

Similar to GoCarb, iSpy is a mobile application, developed by a research group comprised of computer scientists, medical doctors, and RDNs from Toronto, Canada, aimed to test the usability and impact of the application as a carbohydrate counting resource for individuals with Type 1 Diabetes[70]. The research group conducted a pilot randomized control trial in 2020, consisting of 43 participants, ages 10-17 years old from The Hospital for Sick Children, with one arm utilizing the iSpy application for carbohydrate counting and the other following usual care methods[70]. Participants in the intervention group improved accuracy in carbohydrate counting with users reducing the amount carbohydrate estimation errors greater than 10g (P=0.47), and lowering their HbA1c levels (P=.03). Notably, 43% of users continued using the application after the study had ended [70]. This study's main limitation is that the intervention group used the program at their own discretion, which reduced the amount of data that could have been gathered to gauge accuracy in comparison to the control group[70]. Researchers noted that while participants did not complain of issues around the limitation of the database, they recognize this as an area for improvement if it were to be used around the world or in a more diverse cultural setting[70]. iSpy is focused on carbohydrate assessment and does not take into consideration other nutrients which is an area that is worth exploring for future research. The iSpy application currently is only accessible for research and not available for public use. The application's last software update was listed as July 28th, 2018; which may indicate it is no longer being pursued for development.

Recently (2020), researchers from the School of Human Nutrition out of McGill University (Montreal, Quebec, Canada) conducted to assess the validity and test usability of Keenoa, a smartphone image-based dietary assessment application, compared to a 3DFD[68]. The study was for 2 weeks and followed a randomized crossover design, with 72 participants being placed in either the application group or the 3DFD group to start[68]. Participants were healthy adults, free of diseases that may impact dietary intake, did not have a history of eating disorders, and were not in the field of nutrition[68]. During the first week those in the application and 3DFD groups tracked their daily intake through their respective methods for two weekdays and one weekend, then switched methods the following week. The application group would take pre- and post-meal pictures using

Keenoa, where the application used a database to attempt food recognition; if it was unable to identify the food, there was a search function connected to the Canadian Nutrient File that participants would use to manually enter food items[68]. Once food items had been appropriately labeled the participant would estimate the serving size, with any portion that went uneaten being entered in text with the meal photo[68]. Images were then submitted to a RDN to reanalyze themselves to compare to the participant's entry, assessing if food items were missing or portion sizes were incorrect[68]. Keenoa participants' and RDN' data was then compared to each other and the 3DFD group for statistical analysis. When comparing variables between Keenoa participants and RDN, there was agreement on total energy, protein, fiber, and carbohydrate intake but not fat intake; in contrast, there were significant differences in all macronutrient variables between the 3DFD and RDN' data[68]. Later a qualitative study (2021) was performed on the Keenoa cohort, asking participants an open-ended question for feedback on the application[67]. Of the 72 participants that took part in the initial study, only 50 of them provided feedback on the open-end question[67]. The feedback obtained was broken up into three groups: strengths, challenges, and additional recommendations. The strengths of the Keenoa application lie in its ease of use, convenience, faster recording, encouraged mindful eating, and more accurate measures, as participants were less likely to misreport unhealthy meal portions compared to the written 3DFD method[67]. Challenges of the application were errors or inconsistencies in food identification and the bar scanning feature, complex food items commonly unrecognized, limited database, and other glitches with the system[67]. Recommendations for the application included the ability to upload images of food from their camera roll, a better method for capturing food quantity, the option to set up reminders, personalized dietary feedback, the ability to add favorite recipes for quick use, and interest in the integration of smartwatches with the application[67]. The main limitations noted by researchers in these two studies of the Keenoa application were the young demographic of participants and the majority held university degrees (80%), which may not be representative of the population. Overall, researchers found that Keenoa was able to provide accurate information to RDNs for assessment and reduced the burden on the individual while being both time and cost-efficient.[67,68] Currently, the Keenoa application costs $30 a month and is to be used by the RDN as an alternate means of food assessment. The clients of the RDN have free access to the mobile application, but the general population cannot use this resource currently for nutrition tracking.

These applications exhibit the practical application of machine learning and nutrient technology in the areas of dietary assessment and disease management. While most of these studies focused on carbohydrate tracking, there is evidence from these studies that mobile tracking with the use of food image recognition can accurately be used to assess dietary intake and improve disease management. These studies also provided feedback on ways the technology and applications can be used to create a better experience for the users while also addressing the current limitations faced in this area of nutrition technology assessment.

Smart Home Food Recognition Implementation

A laboratory out of Guiyang, China (2022) has developed an autonomous smart home dietary assessment system[71]. This system utilizes a social robot that can move about the space; it uses depth-sensing technology to estimate food volumes and image recognition to not only identify foods but also for facial recognition, matching dietary intake to each user[71]. The system used an expanded image dataset of the ChineseFoodNet[10], which they named CFN-34, for training and testing. They tested the smart home system using multiple scenarios, compounding the number of people and food present with each test, starting with 1 person eating 1-3 different foods and going all the way up to 5 people eating 6-9 different foods[71]. The system used the National Nutrition Database-Food Nutritional Composition Query Platform[72] and Shi An TongFood Nutritional Composition Query Platform[73] to assess food composition and compare accuracy to known values. The results of the study found the system had a response time that ranged from 3.8 - 5.5 milliseconds and nutritional composition accuracy ranged from 80.3% - 97.2% for differing scenarios[71]. With the increase in users and food present response time increased; however, accuracy was less impacted by complexity or users with the most accurate recognition coming in the scenario of 4 people and 4 different foods[71]. The authors of this study recognized several limitations and challenges to the system including: the process for training was time-consuming, the need for improved datasets in the future, the system's inability to autonomously add food and users to the system, and the continued need for improvements in overall accuracy[71]. A limitation not addressed by the authors is the cost of this system or smart home and the social robot, this would limit the access and availability to those of a higher socioeconomic status. In the future, the team would like to focus on the functional design and ability of the social robot, to help cultivate a relationship between the technology and users for opportunities to receive beneficial nutrition feedback[71].

Commercial Food Service Setting

Retail and food service have multiple methods in which they have tracked food waste/loss: direct measurement, waste composition analysis, mass balance, records, diaries, interviews/surveys, and proxy data[74]; however, they can be costly and time-consuming while only collecting data in one form, use of machine learning could potentially combine multiple methods of data collection to better determine how much loss is occurring, the causes and drivers, and action steps to prevent future loss.

Wu et al. (2021), out of Taiwan, sought to address the common problems of long checkout times and questionable accuracy of charges for food, often found in metropolitan cafeteria settings[75]. The team implemented the use of a food recognition and volume estimation system in a bento box buffet to improve efficiency during checkout and better estimation of actual food volumes being purchased[75]. The team created a dataset of 2,025 original sample food images to train the AlexNet, convolutional neural network (CNN) and employed a Kinect depth-sensing camera to obtain volume estimations[75]. The system was accurate and performed food recognition tasks at 0.108 seconds while generating prices; however, the team did not run a comparative study to see the difference in time saved and price variation using technology versus the traditional checkout method[75]. There may be other useful applications for the use of this technology outside of improved checkout times and accurate pricing. In the future, it may be beneficial to utilize this type of system to track food purchasing trends, implement post-meal images to track food waste and provide nutrition feedback to customers to better allow them to make health-conscious choices.

Machine Learnings Food Recognition and Volume Estimation

Both the scope of machine learning and the process of developing a CNN are beyond the focus of this review; however, Won[76] provides detailed information about the process and development of a CNN system being used for food recognition. While there is a growing body of work surrounding the development and process of CNN for food recognition and volume estimations, little work has been done on the application of these nutrition technologies.

Certain requirements need to be met to establish an accurate, functional food recognition system. First, a CNN must be selected, such as AlexNet, Caffe-Reference, GoogleNet, VGGNet-16, VGGNet-19, InceptionV3, or ResNet-50.[16] In many cases, multiple CNN are run on image datasets to better determine which performs recognition most accurate and efficient.[16,77,78] To gauge performance, an image database, like those seen in Table 1.B (References), is selected to run training, validation, and testing on food images. The larger the database and metadata available, the more accurate the recognition; however, there are ways to transform small and medium size image datasets into larger more trainable sets, this can be done by flipping, rotating, cropping, and rescaling images. [76,79] When training the CNN, object detection is performed to locate food in an image, this is achieved similarly to how humans detect certain objects via shape, texture, and color.[77] Once food has been recognized in an image, item segmentation occurs, where the food ingredient is masked in the image to help with labeling, categorization, and volume measurements later down the pipeline; with all labeling and categorization being performed manually entered by experts for data annotations.[80] Once a high level of accuracy and precision in food recognition and categorization occurs the volume measurements can be estimated, this can be achieved in several ways. The least technical way volume estimation is performed is by using object referencing, where a coin or credit card with a known ground truth size is present in the image to then count pixels to determine the surface area of the segmented food.[81] Similar to using a reference card, using known dish dimensions is often used with digital mesh volume measurement, with three-dimensional digital wireframe models being placed over the food item and volume being measured based on the special points of the mesh.[41–44] The most technologically advanced method involves a camera depth sensor that emits infrared light that hits the surface of the food and then bounces back to the sensor to provide time-of-flight data to provide depth mapping for volume calculations.[82] If food item detection, recognition, categorization, and then finally volume estimation are all accurately performed, the data can then be transformed to provide output information on the nutrient content of meals, calories consumed, and food waste.

There are limitations to the capabilities of current food recognition systems. Food states can make food item labeling difficult with foods of similar color being mislabeled when pureed, juiced, julienned, or other processes without some other information being supplied to the system[83]. Along with the foods processed state, there are obstacles in the identification of mixed food states and prepared/cooked foods[84,85], as these are modified and have additional nutrient content added that a camera may not perceive, such as cooking oils or added sugars. Current food image databases are very limited in the variety of foods they can categorize and classify, with most of the datasets being closed for input and limited to research, as seen in Table 1.B. Although there is no single food image database that has been compiled to increase the accuracy and food categorization, Ciocca et al. (2017) have merged the Food-101[15], Food-50[86], VIREO[13], and UECFOOD256[12] databases to create one large food database Food-475[16], with 475 food classes and 247, 636 images. It would be beneficial to have a singular database where researchers could compile standardized food images and metadata to allow for improved CNN performance and a more inclusive, diverse library of dietary selections.

Future Research

Both computer and nutrition science are relatively new sciences in the field of academia. Nevertheless, they have grown and developed at such a steady, rapid rate that they may now provide means to help ameliorate the growing health concerns we face as a society.

As seen in the literature review, most of the progress in this area of technological research has been in the hospital and outpatient settings. In Mikkelsen's editorial piece "Man or machine?", he synthesizes some of the major issues that need to be addressed with future research, which include automation of portion size estimation, correct estimation of leftovers or food waste, more direct links to the nutrient content of foods, better computer vision technology to improve food identification, use of the technology in point of sale operations, privacy concerns around the technology, and collaboration and cooperation between research groups studying the technology[41]. In addition to those key points, there is a need for open access to high-quality nutrition education and useful tools for the general population in all settings, to address the growing challenges of obesity, chronic diseases, food waste, and health equity. The technology we already hold in our hands (smartphones) may be the most cost-effective and expedient tool to provide lasting change in these areas of concern.

While not included in the literature review matrix due to the exclusionary criteria of lacking a functioning prototype and no outcomes data, a team of researchers out of Nebraska (2018) have proposed another useful application concept for food image recognition that could be utilized at the consumer level. This concept when implemented could address the above-mentioned issues and allow for a technology to improve the health of the general population. The team has suggested leveraging food image recognition technology and activity tracking to create an integrated dietary assistant and assessment program[87]. The system monitors real time activity levels to give an energy balance and uses food recognition capabilities to track nutrient intake and provide dietary feedback on ways to manipulate food intake, so as to not overeat.[87] This system may be beneficial with the growing obesity concerns but has certain limitations given the current state of technology and literature including cost of activity trackers, accuracy variance[88], and the lack of widespread use, especially considering that only 21% of Americans wear a tracker as of 2020[89]. The current food image datasets need to continue to grow and accumulate larger, more diverse food choices to better serve diverse populations and be a viable alternative for nutrient tracking. The system also uses a traffic light system[87] to encourage healthier eating, while this can be a beneficial method to improve behavior, it is important to consider its implication on putting a moral value on food and the possible psychological impact of trichotomously labeling foods as good or bad.[90]

There are many opportunities for growth in the field of nutrition and computer science; however, the validation and application of new technologies are very limited in research currently. This problem may be the result of the accelerated evolutionary process of technology development outpacing the ability to put out validated research and allow for societal adaptions of change to occur[91]. Moving forward, the systems put in place need to allow for the growth and expansion of technology so that they are no longer obsolete with every new iteration of technological hardware that is developed.

Suggestions around future research using machine learning should include:

- Using future technologies like light detection and ranging (LiDAR) for accurately measuring food quantities.
- Having standardized measures for image databases allow public input into a system to increase the quantity of data for the machine to learn to grow more rapidly.
- Conduct comparison studies between machine learning systems and current nutrition trackers to gauge the accuracy/reliability.
- Conduct a comparison between groups on whether nutrition intake is improved by using machine learning compared to controls that eat ad libitum.

Concept Proposal for a Future Nutrition Technology Using Food Recognition and Machine Learning for Assessment and Education Purposes

This narrative review's objective was not only to examine the evidence of current applications of nutrition technology, but to synthesize the information provided by these authors and put forward a direction for the development of a fully integrated nutrition technology that can be implemented to overcome the nutrition assessment and education barriers currently faced within the general population.

When developing a novel nutrition technology, both computer scientists and nutrition experts must collaborate to build an effective nutrition tool. The first step in creating a robust and comprehensive system is to create one centralized, open-sourced image dataset; available to researchers and food manufacturers to add and build upon. Similar to Ciocca et al. (2017) merging multiple databases into one[14], would allow for improved accuracy and increased diversity of foods making it more generalizable to varying populations. A CNN can then be selected to be trained on this one dataset with regular, systemic updates as the database grows. Once the system has been set up, integrating the software into either Android and iPhone operating systems using the native camera app would be ideal. This would limit the need to download a third-party app and ensure that every smartphone owner had access to this resource. Google and Apple both currently have camera software used for object recognition called Google Lens[92] and Visual Lookup that is natively integrated into the camera and image processing system, an obvious evolution would be to use it for health and educational purposes. Beyond food recognition, a means for accurately tracking portions consumed and wasted is also needed. The current use references objects and digital wire mesh overlays may be one mean for estimation of food volume by using a known objects volume as a reference point, accurate measures can be obtained[41,43,44]; however, there is now the use of LiDAR cameras[93] which are used to determine the size of a three dimensional object, these are currently only found in iPhones but in the future may exist on all smartphone devices. Once foods have been accurately recognized and portions estimated the information could be referenced against the USDA FoodData Central[94] for nutrient composition and breakdown. The information obtained could then be linked to the user's health app to provide their daily nutrition information, along with nutrition feedback by comparing the intake against the current Dietary Guidelines of America[95]. To improve the accuracy of data collected on complex dishes often found in restaurant establishments when eating out, the system would use image geolocation, and metadata to search the internet for the nutrition information of the dish and amount consumed. The FDA requires establishments with 20 or greater locations to provide nutrition information for their menus.[96] If certain nutrients are being under or overconsumed, the system would alert the user of the dietary pattern and provide nutrition education feedback. The user would set their language and education level in the health application settings to ensure the educational material meets their needs. Similarly, to the suggestion by Silva[87], integrating activity tracking technology into the system would be utilized to promote weight management by giving data on energy balance by analyzing energy intake and energy expenditure. The application would then provide dietary feedback and recommendations based on goals the user has established.

Another technological integration that would be beneficial if integrated into a nutrition system is the use of RFID. Ofei et al. (2018) utilized this technology for patient information tracking in the DIMS 2.0 prototype they developed; however, it is now being used in the food system retail industry to monitor stock, traceability, expiration dates, and food safety[97]. Currently, phones have the ability to read these tags as close as 2-3 meters without having to scan a barcode for the stored information[98]. The use of this technology could be used for consumers to have digital inventories at home without the need to scan every item, providing information on product expiration dates or if there was a recall on a food item they have in their inventory. Along with the use of the inventory, it could serve to provide users with healthy recipes that meet their dietary needs. The system could utilize data mining software to dig thorough internet databases for recipes that use ingredients that users have in stock. The user could select the recipe they want to make and then capture their pre- and post-meal images for nutrient information. Users additionally could set the system to meet a certain dietary preference, such as DASH diet, Mediterranean, Vegan, Gluten Free, allergy considerations, etc.

This system could not only be used for the user's purposes to improve health goals but also in research as a validation method and for nutrition assessments performed by an RDN. The benefit of a system like this is that it takes away the burden of writing down everything eaten, provides a variety of meal options using ingredients already purchased without the need of searching, gives instant feedback on how eating patterns match the current dietary guidelines and how users can improve them, and eliminates recall error when performing nutrition assessments. It also allows for actual intake to be seen that is representative of the users' usual dietary patterns, in comparison to a 24-hr recall or 3-day food record that have limited capabilities. The system can be used both for assessment and intervention purposes by RDN, along with serving as a general health tool for the entire population.

Summary

Nutrition technology is the way of the future for improving public health outcomes, reducing food waste, and alleviating health inequity and the current framework for developing a beneficial nutrition assessment system is promising. Though there has been great improvement in achieving accurate food volume estimations and recognizing a wide variety of ethnic or variably prepared foods, there is still room for improvement. Some hurdles must be overcome regarding achieving accurate food volume estimations and recognizing a wide variety of culturally unique foods and food items in their differing states/prepared forms. Collaborative efforts between those in the field of computer science and nutrition need to create a high-fidelity system that can alleviate the burden that currently weighs on the healthcare system and consumers. When developing these future nutrition technologies, it is important to take into consideration the usability and setting that these technologies will be implemented, with consumer-level applications being simplified for ease of use and adherence. This paper explored the current implementation of these nutrition technologies, their benefit, and limitations, as well as a proof-of-concept application and its own novel application for nutrition technology implementation.

The practical application of this technology in the field of dietetics can be observed in its use for both the inpatient and outpatient settings as demonstrated by the predominance of research in these two realms. However, there is still broad and untapped potential in applying the technology to nutrition counseling and behavior modification. As the understanding of nutrition and technology grows, there will be an increased need for RDNs and other healthcare professionals to utilize the resources available to them and this gives such an opportunity.

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Table 1B. Summary of studies implementing machine learning and nutrition technology in real world settings.

Author, Year	City, Country: Setting	Population	Validation Method	Purpose	Results	Limitations
Alfonsi et al.[70] 2020	Toronto, Canada: The Hospital for Sick Children	Youth age 10-17 years old, Type 1 Diabetes	Validated against Nutrition Facts Panel	Test the usability and accuracy of a carbohydrate counting application in a youth population with Type 1 Diabetes.	iSpy users saw improvement in carbohydrate counting accuracy, reduction of carbohydrate counting error of <10g and lowering of HbA1c levels compared to the control.	Relatively small sample size from one location. Limited food database that may not be reflective to all populations.
Bally et al.[65] 2017	Bern, Switzerland: Bern University Hospital	20 adults, average age 35 years, Type 1 Diabetes	Validated against USDA Nutrient Database	Compare the ability of a carbohydrate counting application to conventional methods to assess overall glucose control	GoCARB use showed significant reduction in time spent hyperglycemic P=0.039.	Small sample size but this was a pilot study. The nutrient recognition and volume estimation was solely carbohydrates.

				in adults with Type 1 Diabetes.		
Bouzo et al.[67] 2022	Montreal, Quebec, Canada: PERFROM Centre, Concordia University	72 adults, >18 years old	Validation against 3-day food records	Analyzing the qualitative data of Keenoa, a smartphone image based dietary assessment tool against 3-day food records.	They collected 72 exit surveys from participants with 50 completing an open-ended question for general feedback. They broke up feedback into 3 categories strengths, challenges, and improvements. Strengths: Picture recognition software, data collection Challenges: Barcode scanning, limited food database, time consuming Improvements:	This study surveyed mostly younger adults with higher education backgrounds (80%) which may not represent the general population.

					Uploading photographs, describe and quantify food, accessible nutritional data	
Ji et al.[68] 2020	Montreal, Quebec, Canada: PERFROM Centre, Concordia University	72 adults, >18 years old	Validation against 3-day food records	Validate the use of Keenoa, a smartphone image based dietary assessment tool against 3-day food records.	Assessing data, it was found that Keenoa participants and Keenoa RDNs had significant agreement for energy, protein, carbohydrates, and fiber. Keenoa comparison to 3-day food record had a range of .04 to .51. They found that 34.1% of participants preferred using the mobile application compared to 9.6% preferring 3-day food records.	This study surveyed mostly younger adults with higher education backgrounds (80%) which may not represent the general population.

Li et al.[71] 2022	Guiyang, China: Guizhou University	N/A	The validated ChineseFoodNet dataset was used for testing	Create a smart home food recognition system to help track users' nutrient consumption for dietary assessment and behavior monitoring purposes.	The smart home model was able to achieve average nutritional composition accuracy of 90.1% with a response time of 6.1 milliseconds	The foods recognition was based on one dataset used and may not apply to all food. The smart home system requires manual addition of food and users into the system.
Lu et al.[64] 2020	USA and Switzerland: N/A	N/A	Validated using USDA and Swiss Nutrient Databases against two multimedia databases: MADiMa[99] and "Fast Food"	Compare a dietary assessment application that utilizes food recognition and volume estimation for nutrient content of meals from pictures to estimations by experienced RDNs.	GoFood outperformed RDN on estimating nutrient content of non-standardized meals and comparable on fast food meals.	Currently only available on Android phones and is limited to research purposes.
Lu et al. [60] 2020	Bern, Switzerland: Bern University Hospital	N/A	5-fold cross validation strategy	An AI based nutrient intake assessment system was developed to	The AI system was able to estimate nutrient intake of > 0.91 of the ground	It is currently computer based limiting its mobility.

				estimate intake of patient's hospital meals using image recognition and depth cameras to estimate food volume.	truth with a mean relative error <20%	
Ofei et al.[45] 2014	Aalborg, Denmark: Aalborg University Hospital	N/A	Tray weights were measured before and after meals to validate intake.	Testing the abilities of a dietary intake monitoring system in the collection of patient intake and food waste.	Prototype of DIMS is able to use photo imaging and weighing to estimate patient waste, food preferences and food intake, it also employs temperature technology to ensure food safety and quality.	The prototype did not have the ability to recognize food or provide nutrient data on intake.
Ofei et al.[58] 2015	Aalborg, Denmark: Aalborg University Hospital	N/A	Tray weights and predefined portion sizes were used in conjunction with "Master Cater" database to validate food	Testing to see if there are varying levels of food waste based on patients' nutritional risk when the patient is allowed to	DIMS is able to use photo imaging and weighting to estimate patient waste, food preferences and food intake, it	The prototype is unable to recognize food and only able to be implemented in closed systems where food and

			waste and nutrient consumption.	select portion size.	also employs temperature technology to ensure food safety and quality. It also is able to cross reference "Master Cater" system employed by the hospital to obtain nutrient intake estimations based on meal consumption.	nutrients are already known.
Ofei et al.[59] 2018	Odense, Denmark: Odense University Hospital	N/A	Validated against weighed food method	Test the reliability and validity of a dietary intake monitoring system versus the weighed food method.	DIMS 2.0 had a significant correlation with the weighed food method, with trained and untrained assessors having high levels of agreement over portion sizes of specific food items in before and after meal photos.	The system cannot recognize food but is not needed to with the closed system where all foods are known and meals are attached to specific patient data profiles when ordering. The DIMS 2.0 is unable to

						weigh individual food items on the plate which could impact the final output of nutrient content consumed.
Rhyner et al.[69] 2016	Bern, Switzerland: Bern University Hospital	19 adults, avg age 40.5 years, Type 1 Diabetes	Validated against USDA Nutrient Database	Compare the accuracy of a carbohydrate counting application prototype to normal performance of estimation by adults with Type 1 Diabetes.	GoCARB users had an absolute error of 12.28 grams carbohydrate compared to 27.89 without the app. The app was able to successfully segment food 75.4% of the time and recognize individual food items 85.1% of the time.	The sample size was small, and error was larger than previously seen in literature. Baseline nutrition knowledge wasn't taken into consideration. The app only looks at carbohydrate quantity and does not include other macronutrients
Vasiloglou et al.[66]	Bern, Switzerland:	N/A	Validated against USDA food	Compare differences in carbohydrate	GoCARB saw similar accuracy in estimation of	The RDNs in this study were viewing images

2018	Bern University Hospital		composition database	estimations by trained RDN versus carbohydrate counting application that utilizes food image recognition and volume estimation.	carbohydrate content of meals compared to RDN with the mean absolute error being 14.8g vs 14.9g	and not the food in person which may have skewed their ability to properly estimate carbohydrate content. Most RDNs were using the carbohydrate exchange list to determine estimates which isn't always precise. Food presented in images did not overlap which in a real-world scenario will not always occur.
Wu et al.[75] 2021	Kaohsiung City, Taiwan: Bento Box Buffet	N/A	K-fold cross validation method	Test the feasibility of a prototype machine with food recognition and volume estimation capabilities on	The bento box system was able to generate a 96.3% accuracy rate in 0.108sec when recognizing foods and was	There was no nutrition output information for consumers.

				improving checkout speeds and accuracy of cost in a Taiwanese bento box buffet.	able to find food volume using Kinect depth camera.	