A Survey on Food Computing

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Food is very essential for human life and it is fundamental to the human experience. Food-related study may support multifarious applications and services, such as guiding the human behavior, improving the human health and understanding the culinary culture. With the rapid development of social networks, mobile networks, and Internet of Things (IoT), people commonly upload, share, and record food images, recipes, cooking videos, and food diaries, leading to large-scale food data. Large-scale food data offers rich knowledge about food and can help tackle many central issues of human society. Therefore, it is time to group several disparate issues related to food computing. Food computing acquires and analyzes heterogenous food data from different sources for perception, recognition, retrieval, recommendation, and monitoring of food. In food computing, computational approaches are applied to address food related issues in medicine, biology, gastronomy and agronomy. Both large-scale food data and recent breakthroughs in computer science are transforming the way we analyze food data. Therefore, a series of works have been conducted in the food area, targeting different food-oriented tasks and applications. However, there are very few systematic reviews, which shape this area well and provide a comprehensive and in-depth summary of current efforts or detail open problems in this area. In this paper, we formalize food computing and present such a comprehensive overview of various emerging concepts, methods, and tasks. We summarize key challenges and future directions ahead for food computing. This is the first comprehensive survey that targets the study of computing technology for the food area and also offers a collection of research studies and technologies to benefit researchers and practitioners working in different food-related fields.

CCS Concepts: • **General and reference** → **Surveys and overviews**; • **Information systems** → **Multimedia information systems**; *Information retrieval*; • **Applied computing** → **Health care information systems**;

Additional Key Words and Phrases: Food computing, food recognition, health, food perception, food retrieval, recipe analysis, recipe recommendation, monitoring, survey

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1 INTRODUCTION

Food has a profound impact on human life, health and wellbeing [Achananuparp et al. 2018; Nordstrom et al. 2013]. An increasing amount of people is becoming overweight or obese. According to WHO, there are more than 1.9 billion adults aged 18 or over with overweight, where more than 650 million ones are obese. The worldwide prevalence of obesity in 2016 is nearly three times that of 1975[1]. Overweight and obesity have been found to be one of major risk factors for various chronic diseases, such as diabetes and cardiovascular diseases[2]. For example, it is estimated that 415 million people suffers from diabetes worldwide in 2015[3]. One important reason is that many generally maintain an excessive unhealthy lifestyle and bad dietary habits [Ng et al. 2014], such as the increased intake of food with high energy and high fat. In addition, food is much more than a tool of survival. It plays an important role in defining our identity, social status, religious significance and culture [Harris 1985; Khanna 2009]. Just as Jean Anthelme Brillat-Savarin said, "tell me what you eat, and I will tell you who you are". Furthermore, how we cook it and how we eat it are also factors profoundly touched by our individual cultural inheritance. For these reasons, food-related study [Ahn et al. 2011; Bucher et al. 2013; Canetti et al. 2002; Chung et al. 2017; Sajadmanesh et al. 2017] has always been a hotspot and received extensive attention from various fields.

In the earlier years, food-related study has been conducted from different aspects, such as food choice [Nestle et al. 1998], food perception [Sorensen et al. 2003], food consumption [Pauly 1986], food safety [Chen and Tao 2001] and food culture [Harris 1985]. However, these studies are conducted using traditional approaches before the web revolutionized research in many areas. In addition, most methods use a small-scale data, such as questionnaires, cookbooks and recipes. Nowadays, the fast development of various networks, such as social networks, mobile networks and IoT allows users to easily share food images, recipes, cooking videos or record food diary via these networks, leading to large-scale food dataset. These food data implies rich knowledge and thus can provide great opportunities for food-related study, such as discovering principles of food perception [Mouritsen et al. 2017], analyzing culinary habits [Sajadmanesh et al. 2017] and monitoring the diet [Chung et al. 2017]. In addition, various new data analysis methods in network analysis, computer vision, machine learning and data mining are proposed. Recent breakthroughs in Artificial Intelligence (AI), especially deep learning [LeCun et al. 2015] have further fueled the interest in large-scale food-oriented study [Chen et al. 2017c; Hassannejad et al. 2016; Kawano and Yanai 2014b; Pandey et al. 2017] for its superiority in learning representations from various types of signals.

Taking these factors into consideration, we come up with a vision of food computing, which aims to apply heterogeneous food data collected from different data sources to various applications in different fields. To our knowledge, [Harper and Siller 2015] first proposed the term food computing in the agricultural field. However, they didn't give clear definition. In a broad sense, we think that food computing focuses on food-related study via computer science, and it is an interdisciplinary field. Consequently, there are many open questions to answer. For example, what are the core research problems of food computing? What are the key methodologies for food computing? What are representative applications in this domain? What are challenges and potential directions for this research field?

[1] http://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight
[2] http://www.who.int/mediacentre/factsheets/fs311/en/index.html
[3] http://www.diabetesatlas.org/

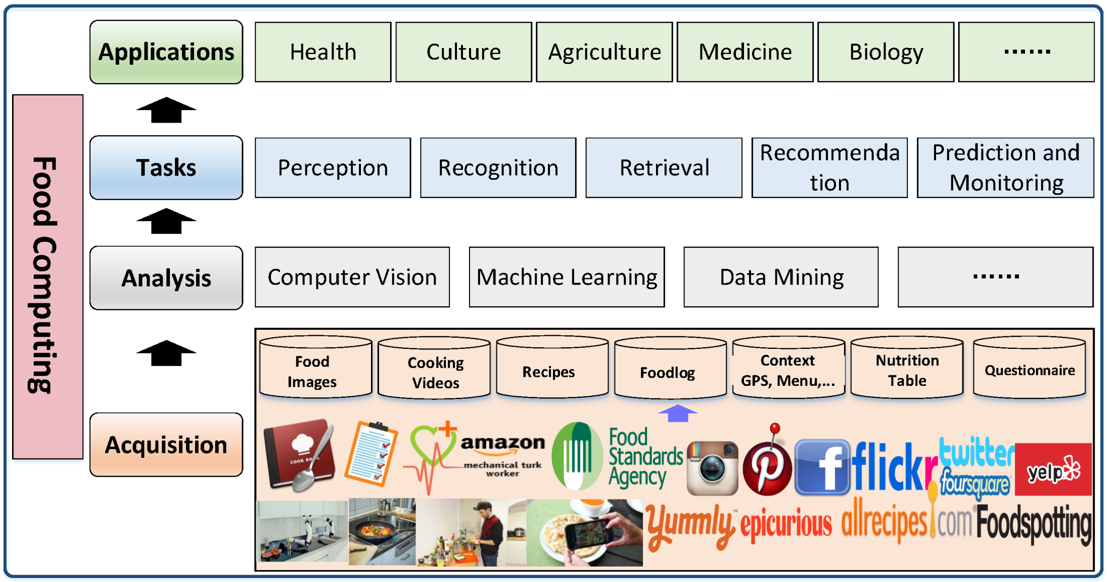

Fig. 1. An overview of food computing.

To answer these questions, we formally define food computing in this article and introduce its general framework, tasks and applications. Some food-related surveys have been done. For example, [Knez and Šajn 2015] gave a survey on mobile food recognition and nine recognition systems are introduced based on their system architecture. [Trattner and Elsweiler 2017a] provided a summary of food recommender systems. [BVR and J 2017] presented a variety of methodologies and resources on automatic food monitoring and diet management system. However, to the best of our knowledge, there are very few systematic reviews, which shape this area well and provide a comprehensive and in-depth summary of current efforts, challenges or future directions in the area. This survey seeks to provide such a comprehensive summary of current research on food computing to identify open problems and point out future directions. It aims to build the connection between computer science and food-related fields, serving as a good reference for developing food computing techniques and applications for various food-related fields. To this end, about 300 studies are shortlisted and classified in this survey.

This survey is organized as follows: Section 2 first presents the concept and framework of food computing. Section 3 introduces food data acquisition and analysis, where different types of food datasets are summarized and compared. We present its representative applications in Section 4. Main tasks in food computing are reviewed in Section 5. Section 6 and Section 7 discuss its challenges and prominent open research issues, respectively. We finally conclude the article in Section 8.

2 FOOD COMPUTING

Food computing mainly utilizes the methods from computer science for food-related study. It involves the acquisition and analysis of food data with different modalities (e.g., food images, food logs, recipe, taste and smell) from different data sources (e.g., the social network, recipe-sharing websites and cameras). Such analysis resorts to computer vision, machine learning, data mining and other advanced technologies to connect food and human for supporting human-centric services, such as human behavior and health. It is a typically multidisciplinary field, where computer science meets conventional food-related fields, like food science, medicine, biology, agronomy, sociology and gastronomy. Therefore, besides computer science, food computing also borrows theories and methods from other disciplines, such as neuroscience, cognitive science and chemistry. As shown in Figure 1, food computing mainly consists of five basic tasks, from perception, recognition, retrieval, recommendation to prediction and monitoring. It further enables applications for various fields.

Food computing applies computational approaches for acquiring and analyzing heterogenous food data from disparate sources for perception, recognition, retrieval, recommendation and monitoring of food to address food related issues in health, biology, gastronomy and agronomy.

Figure 1 shows its general framework. One important goal of food computing is to provide various human-centric services. Therefore, the first step is to collect human-produced food data. We can acquire food data with different types from various data sources. In addition, there are also other specific food datasets available, such as the odor threshold database and the volatile compounds in food database. Based on these food data, we utilize different technologies, such as machine learning and computing vision for food data analysis. After that, we can conduct five main food computing tasks. The flavor and sensory perception of food can govern our choice of food and affect how much we eat or drink. Food perception is multi-modal, including visual information, tastes, smells and tactile sensations. Recognition is one basic task and it is mainly to predict food items such as the category or ingredients from food images. Food-oriented retrieval involves single-modality based retrieval (such as visual food retrieval and recipe retrieval) and cross-modal retrieval, which receives more attention for its applications such as retrieving recipes from food images. Food-oriented recommendation can not only recommend the food people might want to eat, but also provide them with a healthier diet. Food recommendation involves more complex and multi-faceted information. Therefore, it is different from other types of recommendations. Prediction and monitoring are mainly conducted based on the social media, such as monitoring public health.

Furthermore, different tasks are not independent but closely intertwined and mutually dependent. For example, the recognized results can further support retrieval, recommendation and even food perception. When the categories of food images are huge, retrieval-based methods can also be used for food recognition. Prediction from the social media can be helpful for the recommendation task. For example, user's food preference predicted from social media is an important step towards personalized food recommendation.

3 FOOD DATA ACQUISITION AND ANALYSIS

In this section, we introduce frequently used data in food computing and briefly give the summary and comparison on existing food datasets.

Benefitting from the development of the internet and various smart devices, a number of research works focus on studying food perception, pattern mining and human behavior via various data-driven methods [Mouritsen et al. 2017]. For example, in order to analyze user's eating habits for his/her dietary assessment, we should acquire his/her food log data for further analysis. Through the analysis of these food data, we can discover some general principles that may underlie food perception and diverse culinary practice. Therefore, the first step of food computing involves the acquisition and collection of food data. Particularly, we summarize existing data sources into three main types: (1) Websites; (2) Social media and (3) Cameras.

Fig. 2. (a) Some recipes from Yummly (b) Food images from two datasets: ETHZ Food-101 [Bossard et al. 2014] and UEC Food256 [Kawano and Yanai 2014a]

In the early years, researchers mainly obtain food data from official organizations to conduct food-related study. For example, [Sherman and Billing 1999] analyzed 93 traditional cookbooks from 36 counties to find the reason that humans use spices. In order to calculate the food calorie, they should search its energy in the nutrition table provided by official organizations, e.g., United States Department of Agriculture (USDA)[4] and BLS[5]. These data acquisition methods are generally time-consuming, laborious and hard to achieve the large-scale.

The proliferation of recipe-sharing websites has resulted in huge online food data collections. These websites such as Yummly, Meishijie, foodspotting and Allrecipes have emerged over the last several years. Besides basic information, such as the list of ingredients, these recipes are associated with rich modality and attribute information. Figure 2 (a) shows some examples from Yummly. Each recipe includes a list of ingredients, food image, cuisine category, course, flavor and macronutrient composition. Such recipe data with rich types can be exploited to answer various food related questions, such as pattern analysis on ingredient combination from different regions [Ahn et al. 2011; Min et al. 2018] and food recognition [Bossard et al. 2014]. As one representative work, [Sajadmanesh et al. 2017] built a large-scale recipe dataset from Yummly with 157,013 recipes from over 200 types of cuisines for culinary habit analysis. In addition, there are rich social information provided by some recipe websites, e.g., ratings and comments, which can be helpful for tasks like recipe recommendation [Teng et al. 2012] and recipe rating prediction [Yu et al. 2013].

Besides recipe-sharing websites, the social media, such as Twitter, Facebook, Foursquare, Flickr, Instagram and Youtube also provide large-scale food data. For example, [Culotta 2014] examined whether linguistic patterns in Twitter

[4]https://ndb.nal.usda.gov/ndb/
[5]https://www.blsdb.de

correlate with health-related statistics. [Abbar et al. 2015] combined demographic information and food names from Twitter to model the correlation between calorie value and diabetes. In addition to textual data, recent studies [Mejova et al. 2016; Ofli et al. 2017] have used large-scale food images from social media for the study of food perception and eating behaviors.

With the popularity of cameras embedded in smartphones and various wearable devices [Vu et al. 2017], collecting food data directly from cameras is also a common way. For example, researchers begin capturing food images in restaurants or canteens for visual food understanding [Ciocca et al. 2016; Damen et al. 2018]. Besides food images, [Damen et al. 2018] used the head-mounted GoPro camera to collect cooking videos.

In summary, the types of food-related data from different sources are divided into the following several types:

- Recipes: Recipes contain a set of ingredients and sequential cooking instructions. In the earlier research, recipes are collected from cookbooks and manually typed into computers. Currently, recipes can be collected from recipe websites, such as epicurious and Allrecipes. As a result, their numbers have grown exponentially. Such type of data can be embedded in the latent space for recipe analysis to further support various applications [Kim and Chung 2016].
- Dish images: Dish images are the most common multimedia data with rich visual information and semantic content. We can extract meaningful concepts and information to support various applications. Most tasks conduct the visual analysis for food images with the single item. There are also some food image datasets such as UEC Food256 [Kawano and Yanai 2014a] and UNIMIB2016 [Ciocca et al. 2016] with multiple food-items. Figure 2 (b) shows some examples.
- Cooking videos: Nowadays, there are plenty of cooking videos, which can guide person how to cook. They contain human cooking activities and cooking procedure information. Researchers can use such data for human cooking activity recognition and other tasks [Damen et al. 2018].
- Food attributes: Food contains rich attributes, such as flavors, cuisine, taste, smell, cooking and cutting attributes. We can adopt rich food attributes to improve food recognition and other tasks [Chen et al. 2017a; Min et al. 2017a].
- Foodlog: Foodlog records food images, text and other calorie information. With the rapid growth of mobile technologies and applications, we can use the Foodlog app to keep the healthy diet. Some works such as [Kitamura et al. 2008] introduced a food-logging system for food balance estimation.
- Restaurant-relevant food information: Nowadays, more works use restaurant-specific information, such as the menu and GPS information for restaurant-specific food recognition [Herranz et al. 2017] and further food logging [Beijbom et al. 2015].
- Healthiness: More and more people pay attention to the health because of the improved living standard. The healthiness contains rich information, such as the calorie and nutrition. An excessive unhealthy lifestyle and bad dietary habits can trigger overweight, obesity and other diseases. Researcher can use the healthiness of food for automatic food calorie estimation from the food image to keep the healthy diet [Okamoto and Yanai 2016].
- Other food data: Other food data such as the data from cooking books, questionnaire,odor threshold database[6] and food product codes. The data by questionnaire [Thompson et al. 2008] includes diverse forms, such as Food Frequency Questionnaires (FFQ) and Food Cravings Questionnaire (FCQ).

After obtaining the initial food collection, especially from web and social media, the next step is data annotation. One simple way is to directly utilize tags from websites or social media as the annotation. However, such annotations are probably noisy. One probable way is manual annotation by ourselves or nutrition experts [Martin et al. 2012]. However,

[6] http://www.thresholdcompilation.com/

such method is limited to small-scale data. In order to annotate large-scale data, crowd-sourcing is generally used, e.g., Amazon Mechanical Turk (AMT) [Kawano and Yanai 2014a].

Existing Benchmark Food Datasets. Many benchmark and popular food datasets have been constructed and released. Table 1 and Table 2 list main food-related databases in more details, where the number in () denotes the number of categories for the column Num, and particular websites or cameras for the column of Sources. We also give the links for datasets if available. From Table 1 and Table 2, we can see that: (1) The benchmark datasets for food recognition are released frequently. Earlier, researchers focus on the food dataset with few cuisines and small-scale. For example, UEC Food100 [Matsuda and Yanai 2012] consists of 14,361 Japanese food images. Benefiting from the fast development of social media and mobile devices, we can easily obtain more food images. For example, [Rich et al. 2016] released a dataset with 808,964 images from Instagram. In addition, ETHZ Food-101 [Bossard et al. 2014] has been a benchmark food dataset for the food recognition task. (2) There are some restaurant-oriented datasets, such as Dishes [Xu et al. 2015] and Menu-Match [Beijbom et al. 2015]. Such datasets generally contain the location information, such as GPS or restaurant information. (3) Compared with food images, recipes contain richer attribute and metadata information. To the best of our knowledge, Recipe1M [Salvador et al. 2017] is the largest released recipe dataset with 1M cooking recipes and 800K images. Recently, [Semih et al. 2018] released a recipe dataset RecipeQA, which includes additional 36K questions to support question answering compared with other recipe datasets. Some datasets with cooking videos are also released for human-activity recognition and prediction,e.g., recently released EPIC-KITCHENS [Damen et al. 2018].

Summary and Discussion. In this section, we summarized existing food-related data sources into three main types, namely websites (e. g., Yummly, Meishijie, foodspotting and Allrecipes), social media (e.g., Twitter, Facebook, Foursquare, Flickr, Instagram and Youtube) and cameras (e.g., smartphone and point-and-shoot camera). We also listed different types of food data, such as recipes, dish images and food attributes, and finally compared existing food datasets. After initial food data collection, different annotation methods are introduced, such as tags from social media and websites, mannual annotation or crowd-sourcing.

These increasing amount of food-related data presents researchers with more opportunities for food analysis. Such analysis can be conducted not only on these datasets individually, but also multiple datasets jointly. For example, we can analyze the correlation between chemical data and recipes [Ahn et al. 2011] or social media images and obesity [Mejova et al. 2016]. These connections with different kinds of food data can provide us with a new perspective on the study of food from different angles, such as the culinary habits and human behavior.

4 APPLICATIONS IN FOOD COMPUTING

Before introducing core tasks in food computing, we first list a number of applications and summarize them from the following four main aspects: health, agriculture, culture and food science.

4.1 Health

What kind of food or how much we eat is closely related to our health. For example, if we eat too much, we can risk developing multiple types of diseases, such as diabetes and heart disease. Therefore, food-relevant study will benefit various health-oriented applications. Particularly, we introduce four representative food-oriented health applications, including (1) food perception for health, (2) food recognition for diet management, (3) health-aware food recommendation and (4) food-health analysis from social media.

Table 1. Food-related Datasets.

Reference	Dataset Name	Data Type	Num.	Sources	Tasks
[Chen et al. 2009]	PFID	Images with categories	4,545 (101)	Cameras	Recognition
[Joutou and Yanai 2010]	Food50	Images with categories	5,000 (50)	Web	Recognition
[Hoashi et al. 2010]	Food85	Images with categories	8,500 (85)	Web	Recognition
[Chen et al. 2012]	-	Images with categories	5,000 (50)	Web+Cameras	Quantity Estimation
[Matsuda and Yanai 2012]	UEC Food100[1]	Images with categories	14,361(100)	Web	Recognition
[Anthimopoulos et al. 2014]	Diabetes	Images with categories	4,868(11)	Web	Recognition
[Kawano and Yanai 2014a]	UEC Food256[2]	Images with categories	25,088(256)	Web	Recognition
[Bossard et al. 2014]	ETHZ Food-101[3]	Images with categories	10,1000(101)	Web (foodspotting)	Recognition
[Wang et al. 2015]	UPMC Food-101[4]	Images and text with categories	90,840(101)	Web (Google search)	Recognition
[Farinella et al. 2014a]	UNICT-FD889[5]	Images with categories	3,583(889)	Cameras (Smartphone)	Retrieval
[Pouladzadeh et al. 2015]	FooDD[6]	Images with categories	3,000(23)	Camera	Detection
[Meyers et al. 2015]	Food201-Segmented	Images with categories	12,625(201)	Web (e.g., Flickr,Instagram)	Segmentation
[Bettadapura et al. 2015]	-	Images with categories and location	3,750(75)	Cameras	Recognition
[Xu et al. 2015]	Dishes[7]	Images with categories and location	117,504(3,832)	Web (Dianping)	Recognition
[Beijbom et al. 2015]	Menu-Match[8]	Images with categories	646(41)	Cameras (Smartphone,Instamatic)	Food Logging
[Ciocca et al. 2015]	UNIMIB2015[9]	Images with categories	2000(15)	Cameras(Smartphone)	Recognition
[Ciocca et al. 2016]	UNIMIB2016[9]	Images with categories	1,027(73)	Cameras(Smartphone)	Recognition
[Zhou and Lin 2016]	Food-975	Images with categories	37,785(975)	Camera+Web(yelp)	Recognition
[Merler et al. 2016]	Food500	Images with categories	148,408 (508)	Web(e.g.,Bing)+ Social media(Instagram)	Recognition
[Rich et al. 2016]	Instagram800K[10]	Images with tags	808,964(43)	Social media(Instagram)	Recognition
[Singla et al. 2016]	Food11	Images with categories	5,000 (50)	Social media(e.g.,Flickr)	Recognition
[Farinella et al. 2016]	UNICT-FD1200[11]	Images with categories	4,754(1,200)	Cameras(Smartphone)	Recognition and Retrieval
[Ofli et al. 2017]	-	Images with tags	1.9M	Social media (Instagram)	Food Perception
[Liang and Li 2017]	ECUSTFD[12]	Images with rich annotation	2978(19)	Camera(Smartphone)	Calorie Estimation
[Ciocca et al. 2017]	Food524DB[13]	Images with categories	247,636(524)	Web+Camera	Recognition
[Chen et al. 2017e]	ChineseFoodNet[14]	Images with categories	192,000(208)	Web+Camera	-
[Thanh and Gatica-Perez 2017]	Instagram 1.7M	Images with comments	1.7M	Social media (Instagram)	Consumption Patterns Analysis
[Harashima et al. 2017]	Cookpad[15]	Images and recipes	4,748,044	Web(Cookpad)	-

[1]http://foodcam.mobi/dataset100.html/. [2]http://foodcam.mobi/dataset256.html/. [3]http://www.vision.ee.ethz.ch/datasets_extra/food-101/.
[4]http://visiir.lip6.fr/. [5]http://iplab.dmi.unict.it/UNICT-FD889/. [6]http://www.site.uottawa.ca/~shervin/food/.
[7]http://isia.ict.ac.cn/dataset/Geolocation-food/. [8]http://neelj.com/projects/menumatch/. [9]http://www.ivl.disco.unimib.it/activities/food-recognition/.
[10]http://www.eecs.qmul.ac.uk/~tmh/downloads.html. [11]http://www.iplab.dmi.unict.it/UNICT-FD1200/ [12]https://github.com/Liang-yc/ECUSTFD-resized-.
[13]http://www.ivl.disco.unimib.it/activities/food524db/. [14]https://sites.google.com/view/chinesefoodnet/ [15]https://www.nii.ac.jp/dsc/idr/cookpad/cookpad.html

Food Perception for Health. One important aspect determining our food choice and how much we eat/drink is how we perceive food from its certain characteristics, such as whether it is sweet or tasty. An increasing number of researchers studied how we perceive food, both before and during its consumption, and have proved the influence of sensory properties of food on eating behavior [Sorensen et al. 2003]. In addition, multimodal sensory cues can affect the food identification and the guidance of food choice [Mccrickerd and Forde 2016].

Dietary Management for Health. Dietary assessment or food diary [Achananuparp et al. 2018; Cordeiro et al. 2015a,b] provides valuable insights for disease prevention. With the advancement of smart devices and computer vision technologies, more approaches utilize vision methods to process food photos captured by the smart phone for diet management. To our knowledge, the first attempt for food intake analysis from the photo is to measure the food intake in

Table 2. Continued

Reference	Dataset Name	Data Type	Num.	Sources	Tasks
[Rohrbach et al. 2012]	MPII Cooking 2[16]	Cooking videos	273	Cameras	Cooking Activity Recognition
[Stein and Mckenna 2013]	50 Salads[17]	Cooking videos	50	Cameras	Cooking Activity Recognition
[Kuehne et al. 2014]	Breakfast[18]	Cooking videos	433	Cameras	Cooking Activity Recognition
[Damen et al. 2018]	EPIC-KITCHENS[19]	Cooking videos	432	Cameras(GoPro)	Cooking Activity Recognition
[Kinouchi et al. 2008]	-	Recipes	7,702	-	Culinary Evolution
[Ahn et al. 2011]	Recipes56K[20]	Recipes	56,498	Web	Ingredient Pattern Discovery
[Teng et al. 2012]	-	Recipes	46,337	Web (allrecipes)	Recipe Recommendation
[Kim and Chung 2016]	-	Recipes	5,917	Web (Recipesource)	Recipe Analysis
[Chen and Ngo 2016]	Vireo Food-172[21]	Recipes with images and ingredients	110,241(172)	Web	Recipe Retrieval
[Sajadmanesh et al. 2017]	Recipes157K	Recipes with metadata	157K	Web (Yummly)	Cross-region Food Analysis
[Chen et al. 2017b]	Go cooking	Recipes&Images	61,139	Web (xiachufang)	Cross-modal Recipe Retrieval
[Salvador et al. 2017]	Recipe1M[22]	Recipes&Images	1M	Web	Cross-modal Recipe Retrieval
[Min et al. 2017a]	Yummly-28K[23]	Recipes&Images	28K	Web (Yummly)	Cross-modal Retrieval
[Min et al. 2018]	Yummly-66K[24]	Recipes&Images	66K	Web (Yummly)	Cross-region Food Analysis
[Markus et al. 2018]	Recipes242K[25]	Recipes	242,113	Web (Allrecipes)	Recipe Healthiness Estimation
[Semih et al. 2018]	RecipeQA[26]	Recipes	20K(22)	Web (Instructables)	Recipe Question Answering

[16]https://www.mpi-inf.mpg.de/departments/computer-vision-and-multimodal-computing/research/human-activity-recognition/mpii-cooking-2-dataset/
[17]http://cvip.computing.dundee.ac.uk/datasets/foodpreparation/50salads/.[18]http://serre-lab.clps.brown.edu/resource/breakfast-actions-dataset/#Downloads.
[19]https://epic-kitchens.github.io/2018. [20]http://www.yongyeol.com/2011/12/15/paper-flavor-network.html [21]http://vireo.cs.cityu.edu.hk/VireoFood172/.
[22]http://im2recipe.csail.mit.edu/. [23]http://isia.ict.ac.cn/dataset/. [24]http://isia.ict.ac.cn/dataset/Yummly-66K.html.
[25]https://github.com/rokickim/nutrition-prediction-dataset/blob/master/.[26]https://hucvl.github.io/recipeqa

the cafeteria settings, developed by [Williamson et al. 2003]. This method is semi-automatic and involves the participant of registered dietitians. To make the system full-automatic, [Zhu et al. 2010] proposed a dietary assessment system, where images obtained before and after food is eaten, are used to estimate the category and amount of consumed food. Similar methods including single-view reconstruction and multi-view reconstruction for food volume estimation [Dehais et al. 2017; Pouladzadeh et al. 2014] are proposed. Recently, a lot of works focus on calorie estimation from one image [Fang et al. 2018; Meyers et al. 2015]. As representative work, [Meyers et al. 2015] proposed an Im2Calories system, which first localized the meal region from one food photo, and then labeled these segmented regions and estimated their volume. In addition, more works conducted food calorie estimation on mobile devices [BVR and J 2017; Pouladzadeh et al. 2016b] and other wearable devices, such as Kinect and glasses with load cells [Vu et al. 2017]. Recently, researchers designed new sensors to track the diets and count the calories [Strickland 2018].

Health-aware Food Recommendation. Many people are facing the problem of making healthier food decisions to reduce the risk of chronic diseases such as obesity and diabetes, which are very relevant to what we eat. Therefore, food recommendation not only caters user's food preference but should be also able to take user's health into account, leading to heath-aware food recommendation. The core problem for health aware food recommendation is to build the model to balance these two components, and thus is helpful for healthy diet. Recently, many works focus on this topic. For example, [Yang et al. 2017] learned users'preferences from a large food image dataset and projected these preferences for general food items into the domain that meets each individual user's health goals. Considering huge potentials in human health, we will see the surge in health-aware food recommendation field.

Food-Health Analysis from Social Media. We're in an era of social media. As food is indispensable to our life, a great deal of online content is relevant to food. Therefore, a great amount of food information about our culinary habits and behavior from the social media can be explored for food-health analysis. Recent studies have shown that we can use social media to get aggregated statistics about the health of people, such as the health insurance coverage and obesity for public health monitoring [Culotta 2014; Mejova et al. 2016].

4.2 Culture

Food is fundamental to the culture, with food practices reflecting our nationalities and other aspects [Bell 1997; Giampiccoli and Kalis 2012; Harris 1985; Khanna 2009]. An understanding of food culture is indispensable in human communication. This is true not only for professionals in fields such as public health and commercial food services, but is clearly recognized in the global marketplace. Food has also come to be recognized as part of the local culture which tourists consume, as an element of regional tourism promotion and a potential component of local agricultural and economic development [Hall and Hall 2003]. In addition, exploring the food culture can help develop personalized food recommendation considering the aspect of food culture from different urban areas.

For these reasons, the study of culinary cultures began to receive more attention [Ahn et al. 2011; Kim and Chung 2016; Sajadmanesh et al. 2017; Zhu et al. 2013]. [Ahn et al. 2011] identified significant ingredient patterns that indicate the way humans choose paired ingredients in their food. These patterns vary from geographic region to geographic region. For example, the ingredients with shared flavor compounds tend to be combined for North American dishes. [Sajadmanesh et al. 2017] further analyzed and compared worldwide cuisines and culinary habits using larger recipe dataset. However, these works only mined recipe text for analysis, and ignored rich visual information. [Min et al. 2018] recently combined food images with recipes from Yummly for multimodal cuisine summarization to further analyze the culinary cultures. The visual information enables the analysis and comparison of culinary cultures easily and more comprehensively. Besides recipes, social media based food culture analysis has been conducted,such as dietary choice study [Abbar et al. 2015; Ofli et al. 2017]. The prosperity of social media provides opportunities to obtain detailed and complete records of individual food consumption, which will continue revolutionizing the way we understand the culinary culture.

4.3 Agriculture

Food computing can also be used in the agriculture or food products. Food image analysis has great potential for automated agricultural and food safety tasks [Senthilnath et al. 2016; Xiang et al. 2014]. For example, [Jimenez et al. 1999] proposed a recognition system to locate the fruit. Recently, artificial vision systems [Chen et al. 2017c; Hernandez-Hernandez et al. 2017; Lu et al. 2017] have become powerful tools for automatic recognition of fruits and vegetables because of its powerful capacity of feature representation. For example, [Hernandez-Hernandez et al. 2017] presented an image capture, cropping and process for fruit recognition. [Chen et al. 2017c] introduced a deep learning method to extract visual features for counting fruits. In addition, there are some works for natural food product classification,such as tomato ripeness classification [Pabico et al. 2015] and rice variety classification [Chatnuntawech et al. 2018]. All of these works, [Chatnuntawech et al. 2018] developed a non-destructive system, which first used a hyperspectral imaging system to acquire complementary spatial and spectral information of rice seeds, and then used Convolutional Neural Networks (CNNs) [Krizhevsky et al. 2012] to extract features from spatio-spectral data to determine the rice varieties.

It is worth noting that agriculture-oriented food recognition is more similar to visual object recognition, such as fruit recognition. However, it is quite different from dish or ingredient recognition. In contrast to object-like recognition, food typically does not exhibit any distinctive semantic parts. As a result, we should design new recognition methods or paradigms for dish or ingredient recognition.

4.4 Food Science

According to Wikipedia, food science is defined as the application of basic sciences and engineering to study the physical, chemical and biochemical nature of foods and principles of food processing[7]. Food computing provides new methods and technologies for these sub-areas. For example, sensory analysis is to study how human senses perceive food. Food perception uses the Magnetic Resonance Imaging (MRI) to measure brain activity based perception, and thus is often conducted in the lab [Killgore and Yurgelun-Todd 2005]. In contrast, [Ofli et al. 2017] considered this problem as food image recognition from Instagram and showed the perception gap between how a machine labels an image and how a human does. In addition, food perception should be multi-modal and it includes visual and auditory cues, tastes, smells and tactile sensations. Therefore, multi-modal integration is needed. Existing studies [Verhagen and Engelen 2006] focused on this topic from the neuroscience. However, we can resort to deep learning based multimodal learning methods [Srivastava and Salakhutdinov 2012] in computer science to better tackle this problem. Another example is the quality control. Some works [Pabico et al. 2015] used the neural network to automate the classification of tomato ripeness and acceptability of eggs.

5 TASKS IN FOOD COMPUTING

In this section, we introduce each of five main tasks in turn according to Figure 1.

5.1 Perception

As mentioned before, food perception plays an important part in our health. In addition, such study will have great potentials for food and beverage industries, for example, a better understanding of the process used by people to assess the acceptability and flavor of new food products.

Traditional studies on food perception are conducted at the level of brain activity typically in labs. Some works conducted the analysis on the relations between the weight from subjects and food-related stimuli [Killgore et al. 2003; Nenad et al. 2016; Rosenbaum et al. 2008a; Sorensen et al. 2003]. For example, [Nenad et al. 2016] found that both lean and overweight subjects showed similar patterns of neural responses to some attributes of food, such as smell and taste. There are also some works which are more directly related to visual perception of food. For example, [Spence et al. 2010] studied the influence of food color on perceiving the taste and flavor. [Ofli et al. 2017] used the image recognition method to study the relation between how food is perceived and what it actually, namely the food perception gap.

However, our experience of food is multimodal-we not only see food objects, but also hear sounds when chewing, feel its texture, smell its odors and taste its flavors. Therefore, food perception actually involves multi-modalities. When we are chewing food, we can perceive the taste, flavor or texture, which will facilitate our appreciation of food. The senses of taste and smell play a great role in choosing food. Visual information of a food product is essential in the

[7]https://en.wikipedia.org/wiki/Food_science

choice and acceptance of this product, while auditory information obtained during the chewing of food products will help us judge whether a product is fresh or not. Food perception does not just depend on one sense, but should be the result from multisensory integration on various types of signals. For example, [Mccrickerd and Forde 2016] studied the role of multimodal cues including both visual and odor ones in recognizing and selecting food. Particularly, they described the affect of the size of a plate or the amount of food served on the food intake. [Verhagen and Engelen 2006] reviewed existing works on multimodal food perception and its neurocognitive bases.

Summary and Discussion. Food perception has received rapid growth of research interest especially in the neuroscience, cognition and health-related fields. The methodology is being in transition, from neuroscience based methods in the lab to computational ones. However, advanced computer vision and machine learning methods in computer science have not been fully exploited for food perception. For example, one important problem of multimodal food perception is that how multimodal features of food are integrated effectively. A feasible method is to employ existing deep networks, such as [Srivastava and Salakhutdinov 2012] for effective fusion on heterogeneous signals. Note that recently, some works such as [Ofli et al. 2017] are beginning utilizing big data from websites and social media and computer vision from AI for the study of food perception. The fast development of AI and the increasing availability of food data is likely to result in the establishment of new research disciplines, such as "computational food perception".

5.2 Recognition

The widespread use of smartphones and advances in computer vision enabled novel food recognition systems for dietary assessment, which is a key factor to prevent and treat these diseases. Once we recognize the category or ingredients of the meal, we can further conduct various health-related analysis, e.g., calorie intake estimation, nutrition analysis and eating habits analysis. In addition, recognizing food directly from images is also highly desirable for other food-related applications. Take self-service restaurants as an example, food recognition can not only monitor the food consumption, but also automatically bill the grabbed meal by the customer. Finally, for people who would like to get a better understanding of food that they are not familiar with or they haven't even seen before, they can simply take a picture and get to know more details about it.

For these reasons, we have seen an explosion in food recognition algorithms in recent years, which are generally divided into the following two types: (1) single-label food recognition, which targets for food images with only one food-item and (2) multi-label food recognition and detection for food images with multiple food-items. In addition, because of wide use in mobile devices and other sensing devices, we also summarize (3) sensor-based food recognition and monitoring. After food recognition, the following step is generally (4) food portion estimation especially in calorie estimation and other dietary management. We finally introduce (5) personalized food recognition for its applications in personal food logging and recommendation.

5.2.1 Single-label Food Recognition. Most research works on food recognition only considered food images with one food item. Relevant works include both hand-crafted and deep representations for multi-class food recognition.

There are two ways using hand-crafted features, single type of features or the combination of different types. SIFT features [Lowe 2004] are widely used as visual features for food classification [Anthimopoulos et al. 2014; Wu and Yang 2009; Yang et al. 2010]. For example, [Yang et al. 2010] first employed the semantic texton forest to classify all image pixels into several categories and then obtained the pairwise feature distribution as visual features. In contrast, most methods [Joutou and Yanai 2010; Martinel et al. 2015; Nguyen et al. 2014] combine different types of hand-crafted features to enhance the performance of food recognition. For example, [Martinel et al. 2015] used various types of features such as Garbor, LBP and GIST, and then exploited a subset to obtain the optimal ranking performance.

Recently, CNN has been widely used for feature extraction in food recognition and achieves great performance improvement than hand-crafted features. Different types of networks are used in the food recognition task, such as AlexNet [Kagaya et al. 2014], GoogLeNet [Wu et al. 2016], Network-In-Networks (NIN) [Tanno et al. 2016],Inception V3 [Hassannejad et al. 2016], ResNet [Ming et al. 2018], and their combination [McAllister et al. 2018; Pandey et al. 2017]. Recently, [Martinel et al. 2018] combined extracted visual features from wide residual networks (WRNs) [Sergey and Nikos 2016] with ones from their proposed slice network for food recognition. To our knowledge, it achieves the state-of-the-art performance in benchmark datasets due to the high performance of WRNs.

In recipe-shared websites, food images are often associated with other rich content or context information, such as cuisines, ingredients, cooking methods and food calories. Therefore, besides food recognition by the food type, food can be categorized by cuisines and other attributes, such as cuisine classification [Zhang 2011], taste and flavor prediction [Druck 2013]. What's more, different types of food labels, such as food name, food ingredients and other attributes can also be learned simultaneously in a multi-task way. These tasks are very relevant and other tasks are generally helpful for visual feature learning to improve the performance of food recognition. For example, one or some of the following typical tasks, including recognizing food ingredients, classifying cooking methods, classifying restaurants and predicting calorie value are conducted simultaneously with food recognition [Chen and Ngo 2016; Ege and Yanai 2017; Min et al. 2017a; Zhang et al. 2016; Zhou and Lin 2016]. One common way is joint food category and ingredient recognition. For example, [Chen and Ngo 2016] developed different CNN architectures for multi-task learning for both food category and ingredient recognition. [Zhou and Lin 2016] exploited rich ingredients and label relationships through bipartite-graph labels, and then combined bipartite-graph labels and CNN together for both ingredient recognition and dish recognition. Recently, [Aguilar et al. 2019] further proposed a new evaluation metric particularly for multi-task food analysis to simultaneously predict cuisine and food categories. There are also works [Min et al. 2017a; Wang et al. 2015], which fused features from different modalities including images and associated text for food recognition.

In addition, [Kaur et al. 2017] augmented the deep neural network with noisy web food images to improving the performance of food recognition. Benefiting from large-scale food data from social media, some studies [Rich et al. 2016] [Barranco et al. 2016] learned to recognize food image content from social media, such as Instagram and yelp.

5.2.2 Multiple-label Food Recognition and Detection. In real-world scenarios, there may be more than one food item in the image. The first work to recognize multiple-food items from one food image is proposed by [Matsuda et al. 2012]. They first detected candidate regions and then classified them. [Matsuda and Yanai 2012] further exploited the co-occurrence relation information between food items for recognizing multiple-food meal photos. In addition, food detection and segmentation are widely used for images with multiple food items.

Food detection has earlier been considered as a binary classification problem, where the algorithm is used to distinguish whether one given image represents food or not, namely binary food detection [Kagaya et al. 2014; Ragusa et al. 2016]. Both hand-crafted [Farinella et al. 2015a; Kitamura et al. 2009; Miyano et al. 2012] and deep features [Kagaya and Aizawa 2015; Meyers et al. 2015] are adopted. Compared with hand-crafted features, an improvement is achieved via CNN based deep networks [Kagaya et al. 2014]. CNN based methods have been proposed for either feature extraction [Aguilar et al. 2017a; Ragusa et al. 2016] or the whole recognition process [Kagaya and Aizawa 2015; Singla et al. 2016]. For example, [Singla et al. 2016] used the GoogLeNet network for food/non-food classification. In addition to binary food detection, some works such as [Anzawa et al. 2019; Bolanos and Radeva 2017] used the deep network to recognize every food type present based on the detected regions. Different from food detection, food segmentation classifies each pixel from one food image. For example, recent research proposes an automatic weakly supervised method based on CNN [Shimoda and Yanai 2015] or distinct class-specific saliency maps [Shimoda and Yanai 2016]. Besides food recognition by food items, there are some works on multi-label ingredient recognition [Bolanos et al. 2017; Chen et al. 2017d]. As one representative work, [Aguilar et al. 2018] proposed a semantic food detection framework, which consists of three parts, namely food segmentation, food detection and semantic food detection. Food segmentation uses the fully CNNs to produce the binary image, and then adopts the Moore-Neighbor tracing algorithm to conduct boundary extraction. Food detection is achieved by retraining YOLOv2 [Redmon et al. 2016]. Semantic food detection removes errors from food detection by combining results of segmentation and detection to obtain final food detection results.

5.2.3 Sensor-based Food Recognition and Monitoring. Over the last decade, a great variety of mobile devices and other sensors have been developed. Food recognition has been increasingly adapted into these sensors for health-aware applications. One general way is to apply food recognition to mobile devices. This also has other advantages of combined various built-in inertial sensors [Min et al. 2017c] with visual food recognition for monitoring activities of daily living, thus providing more complete information for dietary assessment and management [Kong and Tan 2011; Oliveira et al. 2014; Pouladzadeh et al. 2016a]. For example, [Kawano and Yanai 2015] proposed a mobile food recognition system FoodCam for calorie and nutrition estimation. Recently, deep learning based mobile food recognition methods [Pouladzadeh and Shirmohammadi 2017; Tanno et al. 2016] have been fast developed. For example, [Pouladzadeh and Shirmohammadi 2017] proposed a mobile recognition system that can recognize multiple food items in one meal, such as steak and potatoes for further estimation on the nutrition and calorie of the meal. However, when applying deep learning to mobile devices, some unique problems for mobile food recognition need to be solved, e.g., the complexity and memory requirements of deep learning solutions, and energy consumption. Please refer to [Ota et al. 2017] for more details in mobile deep learning. There are two types of mobile food recognition: client-server mode and client-mode. For the client-server mode, the mobile device is only used to take the picture and transfer it to the cloud, where food image processing is performed via the deep learning network [Merler et al. 2016; Peddi et al. 2017]. For the client mode, food image processing is conducted in the mobile device. In this case, deep networks should be pruned or compressed to make them work in the mobile devices. For example, [Yanai et al. 2016] compressed the deep network using product quantization for object recognition. They [Tanno et al. 2016] then used the compressed deep network for mobile food recognition. With the fast development of smart devices and food-related applications, we will witness more effective and efficient deep networks, such as MobileNets [Howard et al. 2017] and ShuffleNet [Zhang et al. 2017b] for mobile food recognition in the future.

There are also works on food recognition and monitoring in other sensors, such as acoustic-based, motion-based and multimodal methods. For example, [Yang et al. 2016] proposed an application iHearFood, which can use the Bluetooth headsets to analyze the chewing sound for food recognition via a deep network. [Li et al. 2013] presented the design and implementation of a wearable oral sensory system to recognizes human oral activities, such as chewing and drinking via sensing the teeth-motion. [Mirtchouk et al. 2016] used a multi-modal sensing device to combine the in-ear audio, head and wrist motion to more accurately classify the food type. A comprehensive survey on applying wearable sensors for automatic dietary monitoring is introduced in [Schiboni and Amft 2018], and please refer to [Schiboni and Amft 2018] for more details.

5.2.4 Food Portion Estimation. Estimating food portion size or food volume is necessary to estimate an individual's food and energy intake. Existing methods on image based food portion estimation are divided into different types, including video-based or multiple images-based [Kong and Tan 2012; Mingui et al. 2010], two-images based [Dehais et al. 2017] and singe-image based ones [Fang et al. 2018; Meyers et al. 2015]. [Kong and Tan 2012] presented a mobile phone based system, DietCam, which only requires users to take three images or a short video around the meal. Then three-dimensional (3D) models of visible food items will be reconstructed to estimate the volume of the food. [Dehais et al. 2017] proposed a three-stage system to calculate portion sizes using only two images of a dish acquired by mobile devices with three stages. A dense 3D model is built from the two images to further serve to extract the volume of the different items. In contrast, [Meyers et al. 2015] first modeled the correlation between RGB and depth image, and then estimated the depth image from only one image. Finally, they used both RGB and estimated depth information for food volume estimation. Besides the CNNs, the generative adversarial networks are also used for food portion estimation [Fang et al. 2018]. In addition, there are other calibration based techniques for estimating food portion volume [Pouladzadeh et al. 2014]. Although recent methods conducted food portion estimation from a single food image since this reduces a user's burden in the number and types of images that need to be acquired, accurate food portion estimation is still challenging due to large variations on food shapes and appearances.

5.2.5 Personalized Food Recognition. Personalized food image recognition focuses on classifying food images created for each individual user. It is very challenging due to dynamic datasets created by each user often have content with considerable variations between different users, and limited number of samples per person. There are few works in this area. [Aizawa et al. 2013] conducted food image detection and food balance estimation using personal uploaded meal images. One recent work is [Horiguchi et al. 2018], which adopted an incremental learning method to personalize a classifier for each user. Personalized food recognition will receive more attention because of its potentials in personalized food recommendation and multimedia foodlog.

In addition, there are some works on restaurant-specific food recognition. In the restaurant scenario, additional information such as location and menu information is utilized [Aguilar et al. 2018; Bettadapura et al. 2015; Herranz et al. 2017, 2015; Wang et al. 2016]. For example, [Xu et al. 2015] proposed a framework to incorporate geo-location information for dish classification. They trained the geolocalized models using these dish images with geographical locations, menus and dish images. During the test stage, for one query, corresponding geolocalized models are selected and adapted to the query.

Table 3 and Table 4 provides an overview of these approaches with respect to visual features, additional information and recognition type. The classifiers what most methods adopt are SVM or Softmax. Table 5 shows an overview of current performance comparison on benchmark datasets.

5.2.6 Summary and Discussion. Food recognition has been widely studied in various fields, such as computer vision and multimedia. The key of food recognition is to extract discriminative visual features. Early researches on food recognition mainly extracted hand-crafted features. In the recent years, image recognition has undergone a paradigm shift towards using deep learning for its strong capability in feature learning, and food recognition is no exception. Compared with hand-crafted features, deep learning for food recognition has achieved great performance improvement. However, most of existing deep learning methods directly extracted deep visual features via CNNs and ignored characteristics of food images and are thus hard to achieve optimal performance. In contrast to general object recognition, food images typically do not exhibit distinctive spatial arrangement and common semantic patterns. One way to mitigate the problem is to utilize other rich content and context information from websites and social media. In addition, with the fast development of smart devices and sensing technologies, food recognition has been applied into mobile devices and other sensors for health-relevant applications. Consequently, new problems arise, e.g., the complexity and memory requirements of deep learning solutions, and energy consumption when applying deep learning to mobile devices and other sensors, which is still one hot topic and needs further exploration.

Table 3. Summary of Food Recognition Using Conventional Visual Features

Reference	Visual Features	Additional Information	Recognition Type
[Bolle et al. 1996]	Texture, Color	-	Food recognition
[Puri et al. 2009]	Color, Textures	-	Mobile food recognition
[Wu and Yang 2009]	SIFT	-	Food recognition
[Joutou and Yanai 2010]	SIFT,Color, Texture	-	Food recognition
[Yang et al. 2010]	Pairwise Local Features Joint Pairwise Local Features	-	Food recognition
[Zong et al. 2010]	SIFT, Texture	-	Food recognition
[Bosch et al. 2011]	SIFT, Color, Texture	-	Food recognition
[Zhang 2011]	Color, Texture	-	Cuisine classification
[Matsuda and Yanai 2012]	SIFT, Color, HoG, Texture	-	Food recognition
[Matsuda et al. 2012]	SIFT, Color HoG, Texture	-	Food recognition
[Farinella et al. 2014b]	Texture	-	Food recognition
[Nguyen et al. 2014]	SIFT, Texture, Shape	-	Food recognition
[Anthimopoulos et al. 2014]	SIFT, Color	-	Food recognition
[Oliveira et al. 2014]	Color, Texture	-	Mobile food recognition
[Kawano and Yanai 2014c]	HoG, Color	-	Mobile food recognition
[Farinella et al. 2015a]	SIFT, Texture, Color	-	Food recognition
[Martinel et al. 2015]	Color, Shape, Texture	-	Food recognition
[Bettadapura et al. 2015]	SIFT, Color	Location & Menu	Restaurant-specific food recognition
[Farinella et al. 2015b]	SIFT, SPIN	-	Food recognition
[Kawano and Yanai 2015]	SIFT, Color, HoG	-	Mobile food recognition
[Ravl et al. 2015]	HoG, Texture, Color	-	Mobile food recognition
[Martinel et al. 2016]	SIFT, Color, Shape, Texture	-	Food recognition
[He et al. 2017]	Texture	-	Food recognition
[Zheng et al. 2017]	SIFT, Color	-	Food recognition

5.3 Retrieval

These massive amounts of data shared on various sites allow gathering food-related data such as recipes, food images and cooking videos. A food-relevant retrieval engine is necessary to obtain what we need. In real applications, the number of examples needed to train a food classifier may not be always available. In this case, food retrieval can be used to find similar foods among available ones and to suggest a possible food type. In health-oriented applications, predicting nutrition content and calorie information from food images requires fine-grained ingredient recognition. However, directly recognizing ingredients is sometimes challenging, since ingredients from prepared food are mixed and stirred. In this case, we can retrieve recipes based on the image query, namely cross-modal retrieval.

According to retrieval types, food-relevant retrieval consists of three types: visual food retrieval, recipe retrieval and cross-modal recipe-image retrieval.

Table 4. Summary of Food Recognition Using Deep Visual Features

Reference	Visual Features	Additional Information	Recognition Type
[Kawano and Yanai 2014b]	HoG, Color, CNN	-	Food recognition
[Kagaya et al. 2014]	AlexNet	-	Food recognition
[Ao and Ling 2015]	GoogleNet	-	Food recognition
[Yanai and Kawano 2015]	AlexNet	-	Food recognition
[Christodoulidis et al. 2015]	CNN	-	Food recognition
[Wang et al. 2015]	VGG	Text	Recipe recognition
[Xu et al. 2015]	DeCAF	Location	Restaurant-specific food recognition
[Herranz et al. 2015]	DeCAF	Location	Restaurant-specific food recognition
[Herruzo et al. 2016]	GoogleNet	-	Food recognition
[Wang et al. 2016]	CNN	Location	Restaurant-specific food recognition
[Singla et al. 2016]	GoogleNet	-	Food recognition
[Ragusa et al. 2016]	AlexNet, VGG, NIN	-	Food recognition
[Wu et al. 2016]	GoogleNet	-	Food recognition
[Ciocca et al. 2016]	AlexNet	-	Food recognition
[Liu et al. 2016]	Inception	-	Food recognition
[Hassannejad et al. 2016]	Inception	-	Food recognition
[Tanno et al. 2016]	Network In Network	-	Mobile food recognition
[Chen and Ngo 2016]	VGG	Ingredients	Multi-task food recognition
[Zhang et al. 2016]	Designed network	Cooking method labels	Multi-task food recognition
[Wang et al. 2016]	Designed network	Restaurant labels	Multi-task food recognition
[Ege and Yanai 2017]	VGG	Food calories	Multi-task food recognition
[Min et al. 2017a]	DBM	Cuisine,Course	Multi-task cuisine recognition
[Aguilar et al. 2019]	VGG,ResNet	Cuisine,Dish	Multi-task food analysis
[Herranz et al. 2017]	AlexNet	Location & Menu	Restaurant-specific food recognition
[Bolanos and Radeva 2017]	GoogleNet	-	Food recognition
[Pandey et al. 2017]	AlexNet, GoogLeNet ResNet	-	Food recognition
[Chen et al. 2017e]	ResNet-152, DenseNet VGG-19	-	Food recognition
[Termritthikun et al. 2017]	NUInNet	-	Food recognition
[Kaur et al. 2017]	Inception-ResNet	-	Food recognition
[Pan et al. 2017]	AlexNet, CafffeNet RestNet-50	-	Ingredient classification
[Aguilar et al. 2017b]	InceptionV3, GoogLeNet ResNet-50	-	Food recognition
[McAllister et al. 2018]	ResNet-152, GoogleNet	-	Food recognition
[Ming et al. 2018]	ResNet-50	-	Mobile food recognition
[Martinel et al. 2018]	WISeR	-	Food recognition

For food image retrieval, image retrieval based on local descriptors (e.g., SIFT) has been extensively studied for over a decade due to their advantage in dealing with image transformations. For example, [Kitamura et al. 2009] proposed a FoodLog system to retrieve personal food images via the combination of BoF visual features and SVM. Compared with [Kitamura et al. 2009], [Aizawa et al. 2014] improved the food image retrieval system by supporting both image-based and text-based query. Some works such as [Farinella et al. 2016] further improved the performance of food image

Table 5. Performance Comparison on the Accuracy in Three Benchmark Datasets (%).

Reference	UECFood100	UECFood256	ETHZ Food-101
[Kawano and Yanai 2014b]	72.26	-	-
[Kawano and Yanai 2014c]	-	50.10	-
[Ravl et al. 2015]	53.35	-	-
[Martinel et al. 2015]	80.33	-	-
[Yanai and Kawano 2015]	78.77	67.57	70.41
[Ao and Ling 2015]	-	-	78.11
[Wu et al. 2016]	-	-	72.11
[Liu et al. 2016]	76.30	54.70	77.40
[Martinel et al. 2016]	84.31	-	55.89
[Hassannejad et al. 2016]	81.45	76.17	88.28
[Zheng et al. 2017]	70.84	-	-
[Bolanos and Radeva 2017]	-	63.16	79.20
[Aguilar et al. 2017b]	-	-	86.71
[Pandey et al. 2017]	-	-	72.12
[McAllister et al. 2018]	-	-	64.98
[Martinel et al. 2018]	**89.58**	**83.15**	**90.27**

retrieval through the combination of different types of features, such as SIFT and Bag of Textons. Recently, image retrieval based on CNN have attracted increasing interest and demonstrated impressive performance. For example, [Ciocca et al. 2018] adopted CNN-based features for food image retrieval, where different types of neural networks (e.g.,VGG and ResNet) are used.

For recipe retrieval, the first step is generally to change the cooking instructions into structured representation for recipe representation. For example, [Wang et al. 2008] modeled cooking instructions from Chinese recipes as graphs, and further designed a novel similarity measurement to support efficient recipe searching. Recently, [Chang et al. 2018] changed the recipe instruction into a tree-structure representation for recipe similarity calculation. In contrast, another type of methods is to fuse different types of recipe-relevant features, such as cooking flow features, eating features and nutrition features [Xie et al. 2011]. [Barlacchi et al. 2016] introduced a search engine for restaurant retrieval based on dishes one user wants to taste rather than using their general categories (such as Japanese and Italian). Finer-grained food properties, e.g., a particular way to cook a dish along with its specific ingredients are considered.

Besides food/recipe retrieval, different neural networks are designed to multimodal embedding for cross-modal recipe-image retrieval, such as attention network [Chen et al. 2017b] and multi-modal deep Boltzmann machine [Min et al. 2017a]. Another method for cross-modal retrieval is to use a hybrid neural network architecture, which jointly learned shared space via image and recipe embedding, where visual features are learned by CNN while recipe text features are sequentially modeled by Long-Short Term Memory (LSTM) [Carvalho et al. 2018; Salvador et al. 2017]. As one representative work, [Salvador et al. 2017] proposed a joint embedding model. There are mainly two components for a recipe, namely ingredients and cooking instructions. For ingredients, they first extracted the ingredient name using bi-directional LSTM [Schuster and Paliwal 1997]. Then each ingredient name is represented via the word2vec model [Mikolov et al. 2013]. Finally, a bidirectional LSTM model is again used to encode these ingredients to the feature representation. For the cooking instruction, they utilized LSTM to encode it to a fixed-length feature representation. These two kinds of representations are concatenated to the final recipe representation. For the image representation, two deep convolutional networks, namely VGG-16 and Resnet-50 models are adopted to extract visual features. Additional semantic regularization on the embedding is further introduced to improve joint embedding.

Table 6. Summary of Main Retrieval Methods

Reference	Data type		Dataset Name	Task
	Image	Text		
[Wang et al. 2008]	-	Cooking graph	Cooking graph database	Recipe retrieval
[Kitamura et al. 2009]	Food images	-	Foodlog	Food retrieval
[Xie et al. 2011]	-	Cooking graph	-	Recipe retrieval
[Barlacchi et al. 2016]	-	Dish name & Ingredients	Food Taste Knowledge Base (FKB)	Recipe retrieval
[Farinella et al. 2016]	Food images	-	UNICT-FD1200	Food retrieval
[Chen and Ngo 2016]	Food images	Ingredients	VIREO Food-172	Cross-modal retrieval
[Chen et al. 2017b]	Food images	Ingredients	-	Cross-modal retrieval
[Chen et al. 2017a]	Food images	Ingredients	-	Cross-modal retrieval
[Salvador et al. 2017]	Food images	Ingredients & Instructions	Recipe 1M	Cross-modal retrieval
[Min et al. 2017a]	Food images	Ingredients & Attributes	Yummly-28K	Cross-modal retrieval
[Ciocca et al. 2018]	Food images	-	Food524DB	Food retrieval
[Carvalho et al. 2018]	Food images	Ingredients & Instructions	Recipe 1M	Cross-modal retrieval

Table 6 provides a summary of main retrieval approaches with respect to features, dataset and tasks.

Summary and Discussion. In this section, we identified three major types of food retrieval methods, namely food image retrieval, recipe retrieval, and cross-modal recipe-image retrieval. With the profusion of large-scale multimodal recipe collections, cross-modal recipe-image embedding and retrieval have become more attention. Different deep networks are proposed to solve this problem. Despite the progress is made in cross-modal recipe retrieval, the retrieval performance is still very low. One key is incomplete food semantic understanding because of its indistinctive spatial arrangement and irregular semantic patterns, leading to inaccurate correlation between food images and ingredients.

5.4 Recommendation

Food recommendation is an important domain for both individuals and society. Different from other types of recommendation systems, food recommendation involves more complex, multi-faceted and other context-dependent information (e.g. life-style preferences and culture) in predicting what people would like to eat. Taking all these factors into consideration, various recommendation methods are proposed, and are divided into four types [Trattner and Elsweiler 2017a], namely collaborative filtering-based methods, content-based methods, hybrid methods, context-aware methods and health-aware methods.

For content-based methods, recipe oriented recommendation has been extensively studied based on the similarity calculation between content items. For this type of food recommendation, different methods for recipe based content representation are adopted, such as topic model based representation [Kusmierczyk and Norvag 2016], structure based representation [Jermsurawong and Habash 2015] and multi-modal representation with various attributes [Min et al. 2017b].

For collaborative filtering-based methods, classic singular value decomposition [Harvey et al. 2013] and matrix factorization [Ge et al. 2015] have been used widely to model the interaction between user and food items for recommendation. Other methods such as latent Dirichlet allocation and weighted matrix factorization are also used [Trattner and Elsweiler 2017b].

For context-aware approaches, numerous exploratory data analysis has demonstrated that rich context such as gender, time, hobbies, location and cultural aspects is important in food recommendation. For example, [Cheng et al. 2017] proposed to select users and items according to relevant context factors for context-aware food recommendation. In addition, exploring other factors such as culinary cultures can also be helpful for context-aware food recommendation. For example, [Golder and Macy 2011] discovered some universal patterns regarding eating from millions of Twitter messages. Similar spatial-temporal patterns can be discovered by analyzing recipes, such as recipe preference distributions under different temporal intervals and regions [Wagner et al. 2014] [Kusmierczyk and Trattner 2015]. For example, [Silva et al. 2014] analyzed check-ins in Foursquare to identify the cultural difference and similarities across different geographical regions. Such cultural analysis and understanding from recipes and social media can help us develop recommendation mechanisms considering the cultural characterization of specific urban areas.

Health-aware food recommendation is unique. Incorporating health into the recommendation has largely been a recent focus [Markus et al. 2018; Nag et al. 2017b; Yang et al. 2017]. Such method not only caters to user's food preference but should be also able to take user's health into account. For example, [Nag et al. 2017b] proposed an online personalized nutrition recommendation system, which can identify the healthiest items and recommend them to users based on their health data and environmental context. Recently, [Markus et al. 2018] used different kinds of features from a recipe's title, ingredient list and cooking directions, popularity indicators (e.g., the number of ratings) and visual features to estimate the healthiness of recipes for health-aware recipe recommendation.

There are also works on mobile food recommendation [Maruyama et al. 2012] [Phanich et al. 2010]. Other relevant studies in the field of nutrition science have shown that proper nutrition and health labels help people to make better food choice for food recommendation [Sonnenberg et al. 2013].

Summary and Discussion. Food recommendation has been becoming a hot research topic with many approaches proposed to improve the performance and experience of food recommendation from different aspects, such as incorporating rich context, multimodal learning and introducing nutrition information. However, most of existing methods mainly borrow ones from recommendation methods in other fields without considering characteristics of food recommendation, such as complex food preference. However, considering their great commercial potentials, we will look forward to seeing the surge, especially health-aware food recommendation in this research field.

5.5 Prediction and Monitoring

Online social media such as Twitter and Instagram provides its users with a way of recording their daily lives, such as dietary choices, leading to large-scale food data. They thus become rich sources to conduct food-related prediction and monitoring.

Many studies have adopted data-driven approaches to predict the income level [Ma et al. 2015], food consumption patterns [Mejova et al. 2015], recipe popularity [Sanjo and Katsurai 2017] and even diseases [Abbar et al. 2015] from these records in the social media. Based on predicted results, using the social media for monitoring public health will naturally be the next step [Capurro et al. 2014]. For example, [Sadilek et al. 2017] prevented the foodborne illness by mining the data in the social media. They applied the machine learning method to Twitter data and developed a system that automatically detected venues likely to pose a public health hazard. [Karisani and Agichtein 2018] detected personal health mentions in Twitter.

Summary and Discussion. We are living in the era of social media, and are leaving digital traces of various types of food-related activities online. Therefore, considering social media as one food social sensor, we can resort social media for food-related prediction and monitoring, such as food consumption analysis and personal health mention prediction. However, it also presents researchers with some challenges, such as much noise and the sheer size of food data. Therefore, we expect more scalable data-driven methods for solving these problems in the future.

6 CHALLENGES

Food computing has received more attention in the last few years for its wide applications. Thus, it is extremely important to discuss existing challenges that form the major obstacles to current progress. This section presents key unresolved issues.

6.1 Food Image Recognition

Robust and accurate food image recognition is very essential for various health-oriented applications, such as food calorie estimation, food journaling and automatic dietary management. However, it is very challenging for the following three reasons: (1) Food images have their own distinctive properties. They don't have any distinctive spatial layout. Although some food categories such as fruits, hamburgers and pizzas have regular shapes, a large number of food dishes have deformable food appearance and are thus lack of rigid structures. Ingredients can be the constituent part of food. However, ingredients from multiple types of food images are distributed randomly in a plate. Other factors, such as cooking methods also affect the appearance of food ingredients. This makes the task different from other ones like scene recognition, where we can always find some distinctive features such as buildings and trees. Therefore, simply borrowing the methods from object or scene recognition is hard to achieve satisfactory recognition results, especially for real-world applications, not mention to images with multiple-item meals. (2) Food image recognition belongs to fine-grained classification. Similarly, food image recognition encounters the same problem as the fine-grained classification, such as subtle differences among different food categories. However, we can not simply directly use existing fine-grained classification methods, such as [Fu et al. 2017] for food image recognition. The reason is that existing fine-grained categorization methods aim to distinguish between different breeds or species. They generally first discover the fixed semantic parts, and then concatenate the features from both global object and semantic parts as the final representation. Such representation includes not only global features but also more discriminative local features. For example, in the bird classification, some semantic parts, such as head and breast should be first localized. However, the concepts of common semantic parts do not exist in food images. Therefore, we should design a new fine-grained categorization paradigm, which is suitable for food recognition. (3) There is lack of large-scale benchmark food images with more categories. In the computer vision, the release of large-scale ImageNet dataset with the Wordnet ontology has greatly further the development of object recognition [Krizhevsky et al. 2012]. Similarly, the large-scale food dataset is required. There are indeed some benchmark food datasets, such as Food101 [Bossard et al. 2014] and UEC Food256 [Kawano and Yanai 2014c]. However, the categories and number of these datasets are not big enough compared with the ImageNet. In addition, food-oriented dataset construction has its particular challenges. For example, because of the region difference, there are probably several different names for the same dish. Similarly, some dishes are labeled with the same dish name, but actually belong to different dishes with different ingredients. This means that it is harder to build a standard ontology according to the dish name like the Wordnet.

6.2 Vision based Dietary Management System

With the fast development of computer vision and machine learning, more dietary management systems resort to vision-based methods. For example, [Meyers et al. 2015] from Google proposed a system Im2Calories, which can recognize ingredients of the meal from one food image and then predict its calorie account. [Beijbom et al. 2015] from Microsoft and University of California presented a computer vision system for automatically logging the food and calorie intake from food images in the restaurant scenario. However, existing dietary management systems are far from perfect and practical. The reasons derive from two-fold: (1) existing food recognition methods are robust to only few and standard dishes. In real-world scenarios, there are thousands of food categories to recognize. There are still considerable types of food images unavailable in the training set. As a result, the system fails to recognize the food, and then the estimated amount of calories is incorrect. In addition, most existing food recognition methods are not specifically for food images and thus have unsatisfactory recognition performance. (2) Even we recognize the food and localize the food region, we next should estimate the food volume. It is still hard to accurately estimate the volume from one image. Probably we can add the interaction to alleviate these problems, which conversely affect the user experience. Therefore, we should simultaneously solve the above-mentioned problems to enable a robust vision based dietary management system, which is harder to achieve.

6.3 Multiple-Network oriented food data fusion and mining

During the past decade, the influence of social network services on people's daily life has sharply increased. Users participate in different social networks. For example, one user may share food photos in Instagram, upload the recipe to the twitter and perform check-ins in Foursquare. In order to completely predict the health and wellness to deliver better healthcare, the first step is to effectively combine and integrate these food-related multi-modal signals from different social networks. However, the unbalanced data distributions in different networks and different accounts from different networks for each user make the effective fusion more challenging. Most of food-relevant works mentioned previously use only one data source. They may not be enough to gain deeper insights and more complete knowledge from multi-source social media data. Furthermore, besides the social network, there are other types of networks, such as mobile networks and IoT. Therefore, we can obtain diverse signals from these different networks. For example, Fitocracy and MyFitnessPal provide the exercise semantics (i.e., sports activity type). Endomondo can be considered as a rich source of sequential data from wearable sensors and wellness-related ground truth. These mobile devices usually include rich multidimensional context information, such as altitude, longitude, latitude and time. Computing the user's lifestyles needs further integrate these heterogeneous signals in a unified way. To the best of our knowledge, there are few publicly works towards it. Multimodal fusion still faces other challenges. For example, it is difficult to build one model that can exploit both shared and complementary information. In addition, not all the data sources will be helpful for certain food-related tasks in some cases. Among all these fused data sources, picking the useful ones is not an easy task.

6.4 Health-aware Personalized Food Recommendation

Existing methods [Elahi et al. 2017; Harvey et al. 2017] mainly refer to the trade-off for most users between recommending the user what he/she wants and what is nutritionally appropriate, where the healthness of the recipe can be predicted based on multiple cues, such as ingredients and images. However, there are other factors to make health-aware personalized food recommendation challenging, such as complex, multi-faceted, information (e.g., the temporal and spatial context, culture, gender and user preference). Each person is unique and the physical state of each person is different at different moments. To enable more accurate food recommendation, we should monitor their wellness constantly. Although some works [Farseev and Chua 2017] integrated the data from wearable devices and several social networks to learn the wellness profile, the heterogeneous modality fusion is still difficult. Therefore, when developing health-aware personalized food recommendation systems, there are additional issues to consider, which do not arise in other recommendation domains. These include that users may have various constrained needs, such as allergies or life-style preferences, the desire to eat only fruit or vegetarian food.In such cases, existing methods work not well.

6.5 Food Computing for Food Science

Food computing is an inherently multidisciplinary field and its progress is predominantly dependent on support, knowledge and advances in closely related fields, such as food science, biology, gastronomy, neuroscience and computer science. As the performance of contemporary vision systems such as food image recognition is still far from perfect. Further investigations into the mechanisms of human perception on the visual food may be a crucially important step in gaining invaluable insights and relevant knowledge that can potentially inspire the better design of the dietary management. For example, most existing food computing methods mainly focus on the conventional multimodal data analysis and mining. However, food science involves multiple subdisciplines, such as food chemistry and food microbiology. We should cope with new data types (e.g., the chemical forms and the molecules structure in food) and new tasks (such as immunogenic epitopes detection from the wheat). Therefore, current food computing methods must be adapted or even re-designed to handle these new data and new tasks. For example, how to design a multimedia feature learning method to represent new data type, such as special chemical forms or the molecules structure in food? How to design novel food computing methods, which target for new tasks, such as ingredient recognition in the food engineering environment? How to use the food computing method to detect various food-borne illnesses in the food quantity control?

7 FUTURE DIRECTIONS

As mentioned earlier, considerable effort will be required in the future to tackle the challenges and open issues with food computing. Several future directions and solutions are listed as follows.

7.1 Large-scale Standard Food Dataset Construction

Like ImageNet for general objects in the computer vision, a large-scale ontology of ImageNet-level food images is also a critical resource for developing advanced, large-scale content-based food image search, classification and understanding algorithms, as well as for providing critical training and benchmark data for such algorithms. To construct the large-scale food dataset, a feasible method is to combine food image crawling from the social media and manual annotation from the crowd-sourcing platform AMT. In addition, we should consider the geographical distribution of food images, such as different cuisines, to cover the whole world. Each region has their own special cuisines and dishes, there is no food experts to master all the dishes. Therefore, the construction of the large-scale food dataset also should need joint efforts of scientists all over the world.

7.2 Large-scale Robust Food Recognition System

Vision-based food system is very fundamental to various real-world applications, such as the dietary assessment and management system. The first priority is to develop a large-scale robust food recognition system. In recent years, deep learning approaches such as CNNs [Krizhevsky et al. 2012] and their variants (e.g., the VGG network [Szegedy et al. 2015], ResNet [He et al. 2016] and DenseNet [Huang et al. 2017]), have provided us with great opportunities to achieve this goal. Deep learning has the advantage of learning more abstract patterns progressively and automatically from raw image pixels in a multiplelayer architecture than using hand-engineered features. There are indeed some efforts for this direction. For example, [Martinel et al. 2018] proposed a slice convolution network to capture vertical food structure, and combined visual features from the general deep network to achieve the state-of-the art performance. We believe there are other special food structures and properties to explore. If we design the deep model to capture the structures particularly for food images from different aspects, the performance will be further improved. In addition, the constructed large-scale standard food dataset can also be critical to advance the development of food recognition system. There are more than 8,000 types of dishes worldwide according to Wikipedia[8] [Bolanos et al. 2017]. Compared with the large amount of dish types, the number of ingredients is limited. Therefore, one alternative solution is ingredient recognition. Some works [Bolanos et al. 2017; Chen and Ngo 2016] have conducted multi-label ingredient prediction from food images in terms of their lists of ingredients. Ingredient recognition will probably also a solution for offering an automatic mechanism for recognize images for applications in easing the tracking of the nutrition habits, leading to more accurate dietary assessment.

7.3 Joint Deep and Broad Learning for Food Computing

A great amount of food-related data is being recorded in various modalities, such as text, images and videos. It presents researchers with challenges, such as the sheer size of data, the difficulty in understanding recipes, computer vision and other machine learning challenges to study the culinary culture, eating habits and health. Fortunately, the recent breakthroughs in AI, especially the deep learning, provides powerful support for food data analysis from each data source. However, food related entities are from different networks, such as social networks, recipe-sharing websites and heterogeneous IoT sources. Effectively fusing these different information sources provides an opportunity for researchers to understand the food data more comprehensively, which makes “Broad Learning” an extremely important learning task. The aim of broad learning is to investigate principles, methodologies and algorithms to discover synergistic knowledge across multiple data sources [Zhang et al. 2017a]. Therefore, in order to learn, fuse and mine multiple food-related information sources with large volumes and multi-modality, one future direction is to jointly combine deep learning and broad learning from different data sources into a unified multimedia food data fusion framework. Such framework will provide a new paradigm, which is transformed to conventional food-related fields, such as food medicine and food science.

7.4 Food-oriented Multimodal Knowledge Graph Construction and Inference

We can exploit the enormous volume of food related data using sophisticated data analysis techniques to discover patterns and new knowledge. However, in order to support heterogeneous modalities for more complex food-oriented retrieval, Question Answering (QA), reasoning and inference, a more effective method is to build a food-oriented multimodal knowledge graph incorporating visual, textual, structured data, rich context information, as well as their

[8]https://en.wikipedia.org/wiki/Lists_of_foods

diverse relations by learning from large-scale multimodal food data. In natural language processing, some promising results have been shown e.g., Freebase [Bollacker et al. 2008]. Semantic web technologies, e.g., ontologies and inference mechanism have been used for the diabete diet care [Li and Ko 2007]. The study on visual relationships with triplets have been emerging in the area of computer vision, including the detection of visual relationships [Lu et al. 2016; Zhu and Jiang 2018] and generation of the scene graph [Johnson et al. 2015] from images. These technologies are helpful for constructing the visual web [Jain 2015]. Other works such as [Zhu et al. 2015] tried to build a large-scale multimodal knowledge base system to support visual queries, and have been shown as a promising way to construct the food-oriented multimodal knowledge graph. Such multimodal knowledge graph is useful to consistently represent the food data from various heterogeneous data sources. In addition, the reasoning can also be conducted based on the knowledge graph for supporting complex query, QA and multimodal dialog via the inference engines.

7.5 Food Computing for Personal Health

Modern multimedia research has been developed fast in some fields such as art and entertainment, but lags in the health domain. Food is a fundamental element for the health. Food computing is emerging as a promising field for the health domain, and can be used to quantify the lifestyle and navigate the personal health. Recently, some works such as [Nag et al. 2017a; Nitish et al. 2017] have proposed the life navigation system for future health ecosystems, such as the cybernetic health. [Karkar et al. 2017] proposed a TummyTrials app, which can aid a person in analyzing self-experiments to predict which type of food can trigger their symptoms. Food computing will provide principles and methodologies for the integration and understanding of food data produced by users. Combined with other information such as attitudes and beliefs about food and recipes, the person's food preferences, lifestyles and hobbies, we can construct the personal model for personalized and health-aware food recommendation service. Therefore, one important direction is to apply food computing to build the personal model for the health domain.

7.6 Food Computing for Human Behavior Understanding

Earlier studies have demonstrated that the food affects the human behavior [Kolata 1982]. Different food choices lead to different change of behaviors. For example, food additives and unhealthy diet could help to explain criminal behavior alcoholism[9]. There are also some works on the relationship between food and human behavior, such as the eating behavior [Achananuparp et al. 2018; Tsubakida et al. 2017], the brain activity [Rosenbaum et al. 2008b] and cooking activities [Damen et al. 2018; Stein and Mckenna 2013]. For example, [Achananuparp et al. 2018] used the data from MyFitnessPal to analyze healthy eating behaviors of users, who actively record food diaries. Food computing can effectively utilized food-oriented different signals, and thus will provide new methodologies and tools to advance the development in this direction.

7.7 Foodlog-oriented Food Computing

With the widespread use of mobile devices, e.g., digital cameras, smartphones and iPad, people can easily take photos of your food to record their diets. In addition, text-based meal record is also supported. Therefore, foodlogs records users' eating history with multimodal signals, With the economic growth of the world, more people resorts to foodlogs for recording their general diet via the smartphone. Foodlog-oriented food computing will become important for its multifarious applications. (1) Foodlogs are most critical for health. Some works [Waki et al. 2015], [Kitamura et al. 2008]

[9]https://articles.mercola.com/sites/articles/archive/2008/07/29/what-s-in-that-how-food-affects-your-behavior.aspx

[Aizawa and Ogawa 2015] proposed a food-logging system, which is capable of distinguishing food images from other types of images for the analysis of food balance. For example, [Aizawa and Ogawa 2015] have proposed the FoodLog system[10], which can receive access to all sorts of dietary information based on your sent photos by smartphones for the health management. In order to more precisely calculate daily intake of calorie from these multimodal signals, a robust foodlog oriented food recognition is also needed. (2) Foodlogs record what one eats or drinks daily and thus reflect their eating habits. Therefore, mining and analyzing rich foodlog data will enable personalized food recommendation, which can offer healthier options for health-aware food recommendation [Trattner et al. 2017]. In addition, foodlogs record current popular food. We can aggregate the foodlog data with time stamps from millions of uses for food popularity prediction.

7.8 Other Promising Applications in the Vertical Industry

There are also other promising applications for food computing in vertical fields. For example, food computing can enable diverse applications in the smart home field, such as smart kitchen and personal nutrition log. Smart home systems can collect valuable information about users' preferences, nutrition intake and health data via food computing methods, such as food recognition and cooking video understanding. Some existing works, such as [Kojima et al. 2015] utilized the text information to understand the audio-visual scene for a cooking support robot. In the future, we believe that the smart kitchen robot needs more functions, more intelligent multimodal interaction and dialog. Food recognition, recipe recommendation and food-related text processing will work jointly to enable this goal. It will also play an important role in the smart farming. Existing works such as [Chen et al. 2017c; Hernandez-Hernandez et al. 2017] can recognize and count the fruits in the trees. More and more food computing systems will be applied to help detect the illness of the food to guarantee the food safety and quantity. With the development of food computing, it will also be applied into more emerging vertical fields, such as smart retails (especially for the grocery shopping) and smart restaurants.

8 CONCLUSIONS

Food computing is a vibrant interdisciplinary field which aims to utilize computational approaches for acquiring and analyzing heterogeneous food data from disparate sources. With the increasing availability of large-scale food data, more food-oriented computational methods from different fields, such as computer vision and machine learning will be widely used or fast developed to enable the prosperity of food computing. Because of its interdisciplinary nature, it can be applied into many applications and services in various fields, from health, culture, agriculture, medicine to biology. In this survey, we provide an extensive review of the most notable works to date on the datasets, definition, tasks and applications of food computing. It is important to address future challenges based on the knowledge from past works and achievements.

Moving forward, the proposed food computing framework helps researchers understand current research and identify unresolved issues for future research. We also discuss some key challenges, particularly unique in food computing. For example, different from general object recognition, food does not always exhibit distinctive spatial layout and configuration. Therefore, a robust and accurate food image recognition is not trivial and a new food recognition paradigm is vital to handle this. Current food recommendation is still in an initial stage of development and face some challenges, such as dynamic and complex context modeling, accurate and robust food preference learning. Considering these

[10]http://www.foodlog.jp/en

challenges, some promising research directions are suggested, such as large-scale standard food dataset construction, large-scale robust food recognition system, and food computing for foodlogs. These lines of promising directions need further research. Because of huge potentials in human health, culture, behavior and other great commercial applications, we will look forward to seeing the surge in food computing in the future.

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