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 disparate 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, vast amounts of work has 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 Internet of Things (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. 2017b], 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), such as deep learning [Jordan and Mitchell 2015; 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 their 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, such as the human behavior [Kolata 1982], health [Harvey et al. 2017], agriculture [Hernandez-Hernandez et al. 2017], culture [Ahn et al. 2011], medicine [Batt 2007], food security [Barrett 2010] and food science [Ofli et al. 2017]. To our knowledge, [Harper and Siller 2015] first proposed the term food computing, which is particularly used 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?

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[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/

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 concludes 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, IoT and recipe-sharing websites). 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 improving the human health, guiding the human behavior and understanding the human culture. 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 various applications for many fields, such as health, culture, agriculture and medicine.

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 differen types from various data sources, such as cookbooks, social networks, various sensors, IoT and recipe-sharing websites. In addition, there are also other specific food dataset available, such as the odor threshold database and the Volatile Compounds in food database. Based on these food data, we utilize machine learning, computing vision, data mining and other technologies for food data analysis. After that, we can conduct a series of food computing tasks, where food-oriented perception, recognition, retrieval, recommendation, prediction and monitoring together constitute main tasks of food computing. 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.
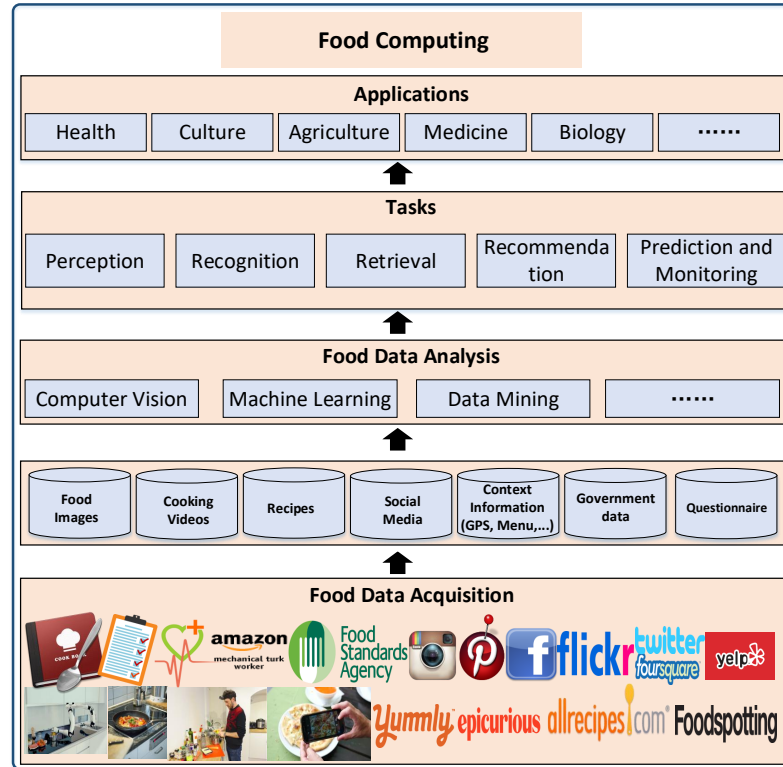
Fig. 1. An overview of food computing.

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 the 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 the retrieval and recommendation tasks. More and more works also resort to the recognition technology for food perception [Ofli et al. 2017]. When the categories of food images are huge, retrieval-based method can also be used for food recognition. Prediction from the social media can also be helpful for the recommendation task. For example,user's food preference predicted from social media will be important information for personalized food recommendation.

3   FOOD DATA ACQUISITION AND ANALYSIS

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

Cuisine American
Course Main Dishes
Flavors
  Sweet: 0.8333 Sour: 0.6667
  Salty: 0.6667 Piquant: 0.3333
  Bitter: 0.6667 Meaty: 0.8333
Nutrition
FAT_KCAL: 110.0
FAPU: 0.49
FOLDFE: 24.8
......
Ingredients
"1 cup ketchup",
"1 tablespoon Worcestershire sauce", "2 teaspoons chili powder",......

Cuisine French
Course Desserts
Flavors
  Sweet: 0.8333 Sour: 0.1667
  Salty: 0.1667 Piquant: 0.0
  Bitter: 0.1667 Meaty: 0.1667
Nutrition
FAT_KCAL: 680.0
FAPU: 8.94
CAMD5: 0.0
......
Ingredients
"3 large eggs",
"8 tablespoons (100 g) sugar, plus extra for sprinkling", ...

Cuisine Italian
Course Main Dishes
Flavor
  Sweet: 0.1667 Sour: 0.8333
  Salty: 0.6667 Piquant: 0.1667
  Bitter: 0.5 Meaty: 0.1667
Nutrition
FAT_KCAL: 770.0
FAPU: 6.8
FOLDFE: 763.43
......
Ingredients
"1 large onion, diced",
"2 red bell peppers, finely diced", "pinch cayenne pepper", ...

Cuisine American
Course Soups
Flavors
  Sweet: 0.5 Sour: 0.5
  Salty: 0.5 Piquant: 0.5
  Bitter: 0.1667 Meaty: 0.5
Nutrition
FAT_KCAL: 120.0
ENERC_KCAL: 290.49
FAT: 12.74
......
Ingredients
"1 large onion, chopped",
"1/2 cup butter",
"2 1/2 cups water",
......

(a)

(b)

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]

Benefitting from the development of the internet and various smart devices, an amount of research work focuses on studying the food perception, pattern mining and human behavior via various data-driven methods [Mouritsen et al. 2017b]. For example, in order to analyze user's eating habit 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 various data sources into five types: (1) official organizations and experts; (2) recipe-sharing websites; (3) social media; (4) IoT devices and (5) crowd-sourcing platforms.

In the early years, researchers mainly obtain food data from official organizations or experts to conduct food-related study. For example, [Sherman and Billing 1999] analyzed the recipes to find the reason that humans use spices using 93 traditional cookbooks from 36 counties. 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]. [Martin et al. 2012] resorted to nutrition experts to label food items. These data acquisition methods are generally time-consuming, laborious and hard to achieve the large-scale.

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

The proliferation of recipe-sharing websites has resulted in huge online food data collections. Many recipe-sharing websites such as Yummly[6], Meishijie[7], foodspotting.com and Allrecipes.com 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, the food image, cuisine category, course, flavor and macronutrient composition. Such recipe data with rich types can be exploited to answer various food related questions. For example, [Ahn et al. 2011] used recipes from three repositories (epicurious.com, menupan.com and Allrecipes) to analyze patterns of ingredient combination based on flavor compounds from different regions. [Bossard et al. 2014] constructed the first large-scale food dataset Food-101 from foodspotting.com for food image recognition. [Sajadmanesh et al. 2017] used large-scale recipes from Yummly with 157,013 recipes from over 200 types of cuisines to analyze worldwide culinary habits. [Min et al. 2018a] further combined food images with rich recipe attribute information from Yummly to analyze and compare culinary cultures in different geographical regions. In addition, there are rich social information provided by some recipe websites, such as Allrecipes and Epicurious, e.g., ratings and comments, which can be helpful for many tasks, e.g., 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, Instagram and Youtube also provide large-scale food data. For example, [Culotta 2014] examined whether linguistic patterns in Twitter correlate with health-related statistics. [Abbar et al. 2015] combined the 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.

Collecting food data from IoT devices is also a common way. With the popularity of cameras embedded in smartphones and various wearable devices [Vu et al. 2017], researchers begin capturing food images in restaurants or canteens for visual food understanding [Ciocca et al. 2016; Damen et al. 2018; Farinella et al. 2014a]. For example, [Ciocca et al. 2016] collected food images in a real canteen using the smart phone. Besides food images, [Damen et al. 2018] used the head-mounted GoPro to record the cooking videos.

There are also some work, which collected food data via crowd-sourcing platforms, such as the Amazon Mechanical Turk (AMT). For example, [Noronha et al. 2011] introduced a system to crowdsource nutritional analysis from photographs using AMT. [Kawano and Yanai 2014a] proposed a framework for automatic expansion based on some food image seeds via the AMT and the transfer learning. [Lee et al. 2017] built a large dataset of less structured food items via crowd-sourcing and conducted the match between the formally structured restaurant menu item and this dataset.

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

- Recipes: Recipes contain a set of ingredients and sequential instructions. In the earlier research, recipes are collected from cookbooks and manually typed into computers. Currently, recipes can be collected from many cooking websites, such as epicurious.com and Allrecipes.com. As a result, their numbers have grown exponentially. Recipes can be embedded in the latent space for recipe analysis and other tasks. For example, [Teng et al. 2012] proposed an ingredient network for recipe recommendation. [Kim and Chung 2016] used the recipes to examine correlations between individual food ingredients in recipes.

- Dish images: Dish images are the most common multimedia data due to their visual information and semantic content. They contain food images with categories, and we can extract meaningful concepts and information via existing deep

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[6] http://www.yummly.com/
[7] http://www.meishij.net/

learning methods for various food tasks. 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 many cooking videos, which can guide person how to cook. They contain human cooking activities and cooking procedure information. Many 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. For example, [Chen et al. 2017a] conducted food recognition and recipe retrieval via predicting rich food attributes, such as ingredient and cooking attributes.

- Food log: Food log records rich information, including 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 the analysis of food balance.

- Restaurant-relevant food information: Nowadays, more and more works use restaurant-specific information, including the menu and GPS information for restaurant-specific food recognition. Such data type includes the dish list from the restaurant. For example, [Xu et al. 2015] utilized the menu data type for discriminative classification in geolocalized settings.

- 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 to keep the healthy diet. For example, [Okamoto and Yanai 2016] proposed a calorie estimation system for automatic food calorie estimation from the food image.

- Other food data: Other food data includes the data from cooking books or the government, questionnaire, odor threshold database[8], food product codes and so on.

Existing Benchmark Food Datasets. Many benchmark and popular food datasets are also 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. We also give the links for datasets if they are available. From Table 1 and Table 2, we can see that

- The benchmark datasets for food image 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 larger amounts of 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.

- 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.

- 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, which contains 1M cooking recipes and 800K food 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

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

the cooking videos are also released for human-activity recognition and prediction, such as recently released EPIC-KITCHENS [Damen et al. 2018].

These increasing amount of food-related data presents researchers with more opportunities for food analysis. Such analysis can be conducted not only on these data sets 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 main four 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 at risk for developing many diseases, such as diabetes and heart disease. Therefore, food-relevant study will benefit various health-oriented applications. We next 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.

4.1.1   Food Perception for Health. How we choose food is very relevant to how we perceive food, e.g., whether it is fresh or tasty. Due to the global overweight and obesity epidemic, an increasing number of researchers studied how we perceive food, both before and during its consumption. For example, [Sorensen et al. 2003] studied the relation between the positive sensory food perception and intake. [Mccrickerd and Forde 2016] focused on how multimodal cues (visual and odor) affected the food identification and the guidance of food choice. [Ofli et al. 2017] used the image recognition method to compared the difference between how a human labels food images and how a machine labels them, and then discovered some facts, such as the positive correlation between the food choice and regions with better health outcomes.

4.1.2   Dietary Management for Health. Dietary assessment or food diary [Achananuparp et al. 2018; Cordeiro et al. 2015a,b; Lydia and David 2008] provides valuable insights for preventing many diseases. Traditional methods mostly rely on questionnaires or self-reporting [Thompson et al. 2008]. These methods have many problems due to underreporting and miscalculation of food consumption. With the development of computer vision methods, more approaches resort to vision-based methods for diet management.

To the best of our knowledge, the first method for food intake analysis of the digital photography is developed by [Williamson et al. 2004, 2003], which measured the food intake in the cafeteria settings. The system used a digital video camera to capture a photograph of a participant's food selection before they eat, and plate waste after they finish eating. These photographs are then analyzed by registered dietitians. These portion size estimates are entered into a custom built computer application that automatically calculates the grams and kilocalories of food selection based on the USDA database. [Martin et al. 2009] further developed a remote food photography method in the natural environment. In contrast, [Noronha et al. 2011] introduced a system PlateMate for crowdsourcing nutritional analysis from photographs of meals.

Table 1. Food-related Datasets.

Reference	Dataset Name	Data Type	Num.	Sources	Tasks
[Chen et al. 2009]	PFID	Images with categories	4,545 (101)	Camera	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+Camera	Quantity Estimation
[Matsuda and Yanai 2012]	UEC Food100[1]	Images with categories	14,361(100)	Web+Manual	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)	Crowd-sourcing	Recognition
[Bossard et al. 2014]	ETHZ Food-101[3]	Images with categories	10,1000(101)	foodspotting.com	Recognition
[Wang et al. 2015]	UPMC Food-101[4]	Images and text with categories	90,840(101)	Google Image search	Recognition
[Farinella et al. 2014a]	UNICT-FD889[5]	Images with categories	3,583(889)	Smartphone	Retrieval
[Pouladzadeh et al. 2015]	FooDD[6]	Images with categories	3,000(23)	Camera	Detection
[Christodoulidis et al. 2015]	-	Images with categories	(572)	Manual	Recognition
[Meyers et al. 2015]	Food201-Segmented	Images with categories	12,625(201)	Manual	Segmentation
[Bettadapura et al. 2015]	-	Images with categories and location	3,750(75)	Web	Recognition
[Xu et al. 2015]	Dishes[7]	Images with categories and location	117,504(3,832)	Dianping.com	Recognition
[Beijbom et al. 2015]	Menu-Match[8]	Images with categories	646(41)	Social media	Food Logging
[Ciocca et al. 2015]	UNIMIB2015[9]	Images with categories	2000(15)	Smart phone	Recognition
[Ciocca et al. 2016]	UNIMIB2016[9]	Images with categories	1,027(73)	Smart phone	Recognition
[Zhou and Lin 2016]	Food-975	Images with categories	37,785(975)	Camera&yelp	Recognition
[Merler et al. 2016]	Food500	Images with categories	148,408 (508)	Web&Social media	Recognition
[Rich et al. 2016]	Instagram800K[10]	Images with tags	808,964(43)	Instagram	Recognition
[Singla et al. 2016]	Food11	Images with categories	5,000 (50)	Social media	Recognition
[Farinella et al. 2016]	UNICT-FD1200[11]	Images with categories	4,754(1,200)	Mobile camera	Recognition and Retrieval
[Ofli et al. 2017]	-	Images with tags	1.9M	Instagram	Food Perception
[Liang and Li 2017]	ECUSTFD[12]	Images with rich annotation	2978(19)	Smart phone	Calorie Estimation
[Ciocca et al. 2017]	Food524DB[13]	Images with categories	247,636(524)	Existing datasets	Recognition
[Muresan and Oltean 2018]	Fruits 360 dataset[14]	Fruit images with categories	71,125(103)	Camera	Recognition
[Hou et al. 2017]	VegFru[xx]	Fruit and vegetable images with categories	160,731(292)	Search Engine	Recognition
[Waltner et al. 2017]	FruitVeg-81[xxx]	Fruit and vegetable images with categories	15,630(81)	mobile phone	Recognition
[Chen et al. 2017e]	ChineseFoodNet[15]	Images with categories	192,000(208)	Web	Recognition
[Thanh and Gatica-Perez 2017]	Instagram 1.7M	Images with comments	1.7M	Instagram	Consumption Patterns Analysis
[Harashima et al. 2017]	Cookpad[16]	Images and recipes	4,748,044	Cookpad	-
[Cai et al. 2019]	BTBUFood-60	Images with bounding-box annotation	52,495	Baidu&Google	Food Object Detection

[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/.
[13]https://www.kaggle.com/moltean/fruits.
[14]https://sites.google.com/view/chinesefoodnet/
[15]https://www.nii.ac.jp/dsc/idr/cookpad/cookpad.html
[xx]https://github.com/ustc-vim/vegfru
[xxx]https://www.tugraz.at/institute/icg/research/team-bischof/lrs/downloads/fruitveg81/

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	Head-mounted GoPro	Cooking Activity Recognition
[Kinouchi et al. 2008]	-	Recipes	7,702	-	Culinary Evolution
[Ahn et al. 2011]	Recipes56K[20]	Recipes	56,498	Recipe websites	Ingredient Pattern Discovery
[Teng et al. 2012]	-	Recipes	46,337	allrecipes.com	Recipe Recommendation
[Kim and Chung 2016]	-	Recipes	5,917	Recipesource.com	Recipe Analysis
[Chen and Ngo 2016]	Vireo Food-172[21]	Recipes with images and ingredients	110,241(172)	Web and manual	Recipe Retrieval
[Sajadmanesh et al. 2017]	Recipes157K	Recipes with metadata	157K	Yummly	Cross-region Food Analysis
[Chen et al. 2017b]	Go cooking	Recipes&Images	61,139	xiachufang.com	Cross-modal Recipe Retrieval
[Salvador et al. 2017]	Recipe1M[22]	Recipes&Images	1M	Cooking websites	Cross-modal Recipe Retrieval
[Min et al. 2017a]	Yummly-28K[23]	Recipes&Images	28K	Yummly	Cross-modal Retrieval
[Min et al. 2018a]	Yummly-66K[24]	Recipes&Images	66K	Yummly	Cross-region Food Analysis
[Markus et al. 2018]	Recipes242K[25]	Recipes	242,113	Crowdsourcing	Recipe Healthiness Estimation
[Semih et al. 2018]	RecipeQA[26]	Recipes	20K(22)	instructables.com	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

These methods are semi-automatic and involve the participant of registered dietitians. To make the system full-automatic, [Zhu et al. 2010, 2008] proposed a technology assisted dietary assessment system, where images obtained before and after foods are eaten, are used to estimate the type and amount of food consumed. Similar methods including sing-view reconstruction and multi-view reconstruction for food volume estimation [Almaghrabi et al. 2012; Chen et al. 2013; Dehais et al. 2017; Pouladzadeh et al. 2014b; Shevchik et al. 2013; Xu et al. 2013] are proposed. Such methods generally need 3D reconstruction from food images.

Recently, a lot of work focused on calorie estimation from one image. For example, [Pouladzadeh et al. 2014a] provided accurate food recognition and calorie measurement by periodically training the system with more food images. [Meyers et al. 2015] proposed an Im2Calories system (Figure 3), which used a segmentation based approach to localize the meal region of the food photo, and then applied the multilabel classifiers to label these segmented regions. Once the system segmented the foods, it can estimate their volume. [Okamoto and Yanai 2016] proposed an image-based
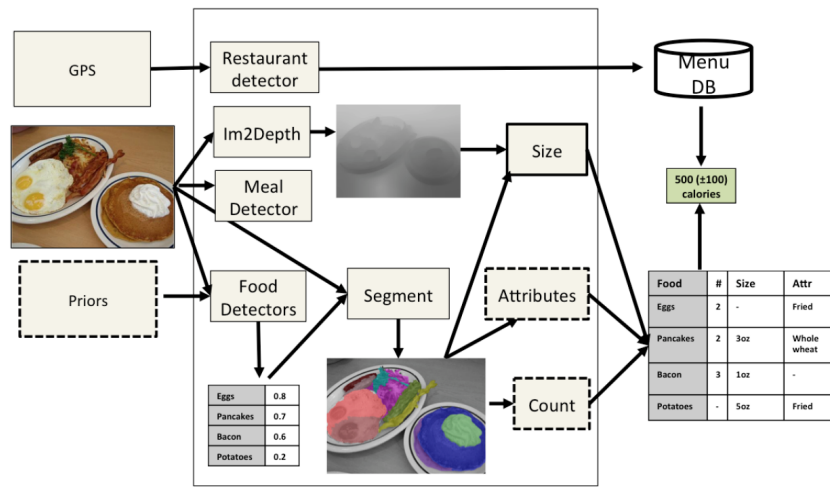
Fig. 3. The framework of Im2Calories [Meyers et al. 2015]

calorie estimation system, which estimates the food calories automatically by simply taking a meal photo from the top with a pre-registered reference object. [Akpa et al. 2017] automatically measured food calories from food photo using ordinary chopsticks as a measurement reference. [Ege and Yanai 2017] estimated the food calorie from a food photo via simultaneous learning of food calories, categories, ingredients and cooking directions using multi-task Convolutional Neural Networks (CNNs)[Krizhevsky et al. 2012]. Recently, [Fang et al. 2018] presented a food portion estimation method to estimate the energy from food images using generative adversarial networks.

Mobile phones are becoming a popular and powerful platform, more works conduct food calorie estimation on mobile devices. Both [Pouladzadeh et al. 2016b] and [BVR and J 2017] gave a survey to present a variety of methods on automated food monitoring and dietary management. Please refer to them in more details. In addition, there are also some works on other devices. For example, [Chen et al. 2012] estimated food categories and volumes by the depth cameras such as Kinect. Several wearable devices, such as glasses with load cells [Chung et al. 2017] or connected to sensors on temporalis muscle and accelerometer [Farooq and Sazonov 2016], have been explored to detect food intake events automatically. The collected information about eating episodes, pertinent to users' diet habit pattern, can serve as a starting point for food consumption analysis and diet interventions, e.g., providing user recommendations for healthier food and eating habit [Faiz et al. 2015]. Please refer to [Vu et al. 2017] in more details on wearable food intake monitoring. Some work [Waki et al. 2015], [Kitamura et al. 2008][Miyazaki et al. 2011] proposed a food-logging system that can distinguish food images from other images, and analyze the food balance. [Aizawa and Ogawa 2015] created a multimedia food-recording tool FoodLog, which offers a novel method for recording our daily food intake for healthcare purposes. [Beijbom et al. 2015] focused on the restaurant scenario and present an automated computer vision system for logging food and calorie intake using images. [Goyal et al. 2017] proposed a project to provide a convenient, visual and reliable way to help users learn from their eating habits and guide them towards better food choice.

Besides food recognition for the dietary management, some researchers designed different sensors to looking to track their diets and count their calories[Strickland 2018]. For example, some researchers have designed the sensor, which can stick to the uneven surface of a tooth to monitor the wearer's glucose, salt, and alcohol intake. [Min et al. 2018b]

explored an audio-kinetic model of well-formed multi-sensory earable devices for dietary monitoring. In addition, there are also some works, which applied constraint reasoning to dynamically adapt dietary recommendations for compensating diet transgressions [Anselma and Mazzei 2015; Anselma et al. 2017, 2018].

4.1.3 Health-aware Food Recommendation. When motivating research on food recommender systems, health problems and improving eating habits are usually mentioned. For example, [Ge et al. 2015a] took calorie counts into consideration in the recommendation algorithm based on their proposed "calorie balance function" that can account for the difference between calories the user needs and ones in a recipe. [Harvey and Elsweiler 2015] realized the trade-off for most users between recommending the user what she wants and what is nutritionally appropriate. [Harvey et al. 2017] employed a post-filtering approach to incorporate nutritional aspects. There is still large space for improving health-aware food recommendation to provide better health service by taking more factors, e.g., the user intake, the estimation of portion size, and other personal factors into account.

4.1.4 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. We upload food photos, find recipes and talk about them. Therefore, a great amount of information about our culinary habits and behavior is being recorded via the social media. Recent studies have shown that we can use social media to get aggregating statistics about the health of people for public health monitoring. For example, [Culotta 2014] presented a large-scale study of 27 health-related statistics, such as the health insurance coverage and obesity. [Fried et al. 2014] collected a large corpus of food-related tweets in Twitter and used all these tweets to predict latent population characteristics such as overweight and diabetes rates. [Abbar et al. 2015] used daily food-related tweets from Twitter to predict the national obesity and diabetes statistics. [Mejova et al. 2015] used the Foursquare and Instagram images to study food consumption patterns in the US, and find the correlation between obesity and fast food restaurants. [Mejova et al. 2016] connected food perception and food images for public health analysis via social media.

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 many 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, more and more work focused on the study of culinary cultures. For example, [Zhu et al. 2013] harnessed online recipes from various Chinese regional cuisines and investigated the similarity of regional cuisines in terms of geography and climate. [Ahn et al. 2011] introduced a flavor network from recipes to identify 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, these ingredients with shared flavor compounds tend to be combined for North American dishes. [Simas et al. 2017] analyzed and discussed a possible new principle behind traditional cuisine: the Food-bridging hypothesis and its comparison with the food-pairing hypothesis using the same dataset and graphical models from [Ahn et al. 2011]. [Strohmaier et al. 2015] proposed an approach to mine cultural relations between different language communities through their description of interest in their own and other
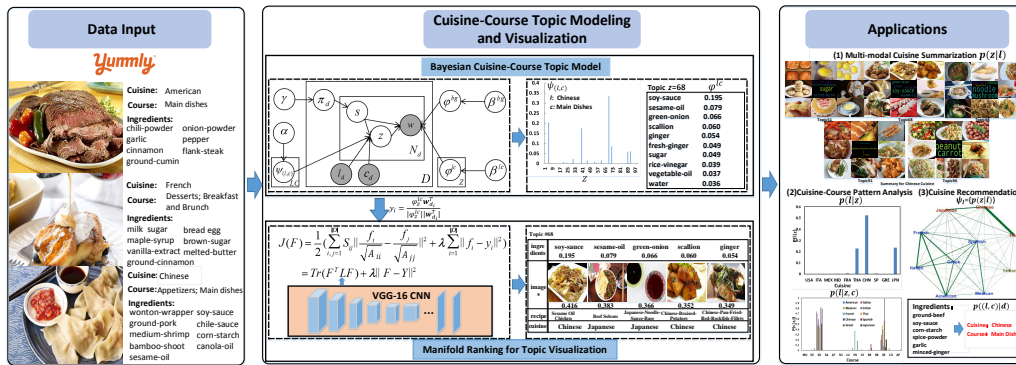
Fig. 4. The proposed culinary culture analysis framework [Min et al. 2018a].

communities' food culture. [Herder et al. 2016] provided large-scale empirical evidence on gender differences in cooking behavior. [Kim and Chung 2016]developed a food analyzer, which used the data from recipes to examine correlations between individual food ingredients in recipes. This paper found that meaningful correlations characterizing the food culture of each area can be explained by these authentic ingredients in recipes. [Sajadmanesh et al. 2017] used large-scale recipes from Yummly to analyze and compare worldwide cuisines and culinary habits.

As representative work, [Min et al. 2018a] recently combined food images with rich recipe attribute information from Yummly for the comparison of culinary cultures. Fig. 4 shows the proposed analysis framework, where the input is recipe information, including food images, ingredients and various attributes (e.g., the cuisine and course) from Yummly. They first proposed a Bayesian topic model to discover cuisine-course specific topics. Based on the learned distribution, they then retrieved relevant food images for topic visualization. Finally, the authors exploited the topic modeling and visualization for cross-region food analysis at both macro-level and micro-level.

Besides recipes, social media based food culture analysis has been conducted for both food culture understanding and popular food culture prediction [Abbar et al. 2015; Ofli et al. 2017]. [Yanai et al. 2009] generated representative geotagged food photographs from typical regions in the world to find the cultural difference. [Silva et al. 2014] used 5 million Foursquare check-ins to find strong temporal and spatial correlation between individuals' cultural preferences and their eating and drinking habits. [Abbar et al. 2015] used tweets from Twitter to study dietary habits. [Ofli et al. 2017] found that the conscious food choices are probably associated with regions of better health outcomes. The prosperity of social media provides opportunities to obtain detailed records of individual food consumption from millions of people, which will continue revolutionizing our understanding of food choice and culinary culture, and their impact on health and well-being.

4.3 Agriculture

Food computing can also be used in the agriculture or food products. Food image analysis has many potential applications for automated agricultural and food safety tasks [Chen et al. 2002; Senthilnath et al. 2016; Xiang et al. 2014]. For example, [Jimenez et al. 1999] proposed a recognition system, which uses a laser range-finder model and a dual color/shape analysis algorithm to locate the fruit. Recently, artificial vision systems have become powerful tools for automatic recognition of fruits and vegetables. For example, [Hernandez-Hernandez et al. 2017] presented the image capture, cropping and process for fruit recognition. [Chen et al. 2017c] introduced a deep learning method to extract visual

features for counting fruits. [Hossain et al. 2019] introduced a deep learning method to extract visual features for automatic fruit recognition for industry applications. [Lu et al. 2017] provided a brief overview of hyperspectral imaging configurations and common sensing modes for food quality and safety evaluation. For natural food product classification, [Patel et al. 1998] proposed a neural network to accurately distinguish between grade A eggs and blood spot eggs. [Pabico et al. 2015] used an artificial neural network to automate the classification of tomato ripeness and acceptability of eggs. [Chatnuntawech et al. 2018] developed a non-destructive rice variety classification system, which used a hyperspectral imaging system to acquire complementary spatial and spectral information of rice seeds, and then used a deep CNN to extract the features from spatio-spectral data to determine the rice varieties. Recently, there are also some work, which uses the visual information to evaluate the food quality[9].

It is worth noting that agriculture-oriented food recognition is more similar to object recognition in the computer vision, such as fruit recognition [Hernandez-Hernandez et al. 2017] and egg classification [Patel et al. 1998]. 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: while we can decompose one object such as bird into some fixed semantic parts, such as head and breast, we cannot find similar semantic patterns from one dish. 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[10]. 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 main tasks of food computing, including perception, recognition, retrieval, recommendation, prediction and monitoring.

5.1   Perception

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. Therefore, the study on food perception plays an important part in our health. In addition, such study will have a number of important potentials for food and beverage industries,

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[9]https://hackernoon.com/your-pizza-is-good-how-to-teach-ai-to-evaluate-food-quality-d835a8c12e86
[10]https://en.wikipedia.org/wiki/Food_science

for example, a better understanding of the process used by people to assess the acceptability and flavor of new food products.

Many studies on food perception are conducted at the level of brain activity typically in labs. For example, [Killgore et al. 2003] found that healthy, normal weight participants are presented with color photographs of food or food-related stimuli differing in caloric value (e.g., high-calorie or low-calorie food) while they underwent blood oxygen-level-dependent functional MRI. [Sorensen et al. 2003] gave a review on the connection between sensory food perception and human eating behavior. [Rosenbaum et al. 2008a] demonstrated that after undergoing substantial weight loss, there are some changes in brain activity because of the elicitation from food-related visual cues for obese subjects. [Nenad et al. 2016] found that both lean and overweight subjects showed similar patterns of neural responses to some attributes of food, such as health and taste.

There are also some work which is 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. The food perception actually involves multi-modalities, including not only visual and auditory cues, but also tastes, smells and tactile sensations. 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 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. Therefore, human food perception is multimodal. For example, [Mccrickerd and Forde 2016] studied the role of multimodal cues including both visual and odor ones in recognizing food 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. In addition, some work such as [Mouritsen et al. 2017a] used the multivariate data analysis method to predict reasonably sensory properties from chemical characterization of sauces.

In summary, food perception has received the rapid growth of research interest especially in the neuroscience, cognition and health-related fields. Most methods are domain-specific. Advanced computer vision and machine learning methods in computer science have not been fully exploited for food perception. Note that recently, some work [Ofli et al. 2017] is beginning utilizing big data from social media and computer vision from AI for the study of food perception. With the fast development of AI and its combination with neuroscience, we believe more and more methods from computer science will be applied to 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 learning networks, such as [Ngiam et al. 2009; Srivastava and Salakhutdinov 2012] for effective fusion on heterogeneous signals.

5.2 Recognition

Diet-related chronic diseases like obesity, diabetes and cardiovascular disease have become a major health concern. Diet management is a key factor to prevent and treat these diseases. Traditional food diary methods manually recorded types and portion of consumed food, and thus the accuracy is hard to guarantee. The widespread use of smartphones and advances in computer vision enabled novel food recognition systems for dietary assessment. 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 of or they haven't even seen before, they can simply took a picture and get to know more details about it.

For these reasons, we have seen an explosion of food recognition algorithms in recent years, which are generally divided into the following four types: (1) single-label food recognition, which targets for food images with only one food-item, (2) multi-label food recognition and detection for food images with multiple food-items, (3) mobile food recognition and (4) restaurant-specific food recognition.

5.2.1 Single-label Food Recognition. Most research works on food recognition assume that only one food item is present in one food image. Relevant works include both hand-crafted [Hoashi et al. 2010; Martinel et al. 2015; Yang et al. 2010] and deep [Kagaya et al. 2014; Martinel et al. 2018; Wu et al. 2016] representations for recognition.

There are two kinds of 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 [Wu and Yang 2009] [Anthimopoulos et al. 2014]. 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 combine different types of hand-crafted features to improve the performance of food recognition. For example, both [Joutou and Yanai 2010] and [Hoashi et al. 2010] fused various types of image features including SIFT, Gabor, and color histograms via the multiple kernel learning for food recognition. For example, [Nguyen et al. 2014] exploited both local LBP features and global structural information of food objects. [Martinel et al. 2015] used many 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 conventional ones [Krizhevsky et al. 2012]. Different types of networks are used in the food recognition task. For example, [Kagaya et al. 2014] applied the AlexNet network [Krizhevsky et al. 2012] to extract visual features for food recognition. [Kawano and Yanai 2014b] integrated CNN features with conventional features as the final feature representation. [Yanai and Kawano 2015] examined the effectiveness of the Alexnet network for food recognition task with pre-training and fine-tuning. [Wu et al. 2016] leveraged hierarchical semantics for food recognition based on joint deep feature learning from GoogLeNet and semantic label inference. [Tanno et al. 2016] used a multi-scale Network-In-Networks (NIN) [Lin et al. 2014] to extract visual features for classification. [Hassannejad et al. 2016] fine-tuned the Inception V3[11] for classifying food images. [Ming et al. 2018] used the Resnet-50 [He et al. 2016] to extract visual features for food recognition and nutrition analysis. [Pandey et al. 2017] proposed CNN based ensemble network architecture including the AlexNet, GoogLeNet and Resnet for food recognition. [McAllister et al. 2018] combined deep residual network features with different supervised machine learning algorithms to classify food images on diverse food image datasets. [Martinel et al. 2018] combined the extracted visual features from the wide residual networks (WRNs) [Sergey and Nikos 2016] with ones from their proposed slice network for food recognition. Figure 5 shows the WISeR architecture, which consists of two branches: a residual network branch and a slice branch network with slice convolutional layers. The residual network is to capture general visual features while the slice branch network is to capture specific vertical food layers. The output of two branches is fused via the concatenation and then fed to two fully connected layers for food classification. To the best of our knowledge, the performance of this
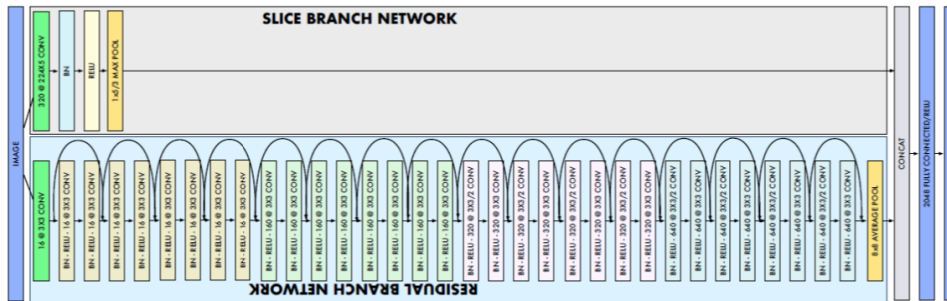

Fig. 5. The WISeR architecture for food recognition [Martinel et al. 2018]

method has achieved the state-of-the-art on benchmark datasets. In addition, some work such as [Wang et al. 2015] focused on feature fusion from different modalities including images and associated text for food recognition.

Besides food recognition by the food name, food can be categorized by the cuisine. For example, [Zhang 2011] represented ingredients as attributes in the first layer and the cuisine as categories in the second layer, then adopted an attribute-based classifier like [Lampert et al. 2009] for cuisine classification. [Su et al. 2014] treated the ingredients as features and constructed different classifiers to predict cuisine labels of recipes. [Min et al. 2017a] utilized a multimodal deep Boltzmann machine to explore both visual and ingredient information for multi-modal recipe classification. In addition, [Druck 2013] utilized various information from the recipe, including the title, a set of ingredients and an ordered list of preparation steps for recipe attribute (such as tastes and flavors) prediction.

In addition, some work [Ao and Ling 2015; Horiguchi et al. 2018; Maruyama et al. 2010] focused on incremental learning for food recognition. [Kaur et al. 2017] augmented the deep model with noisy web food images to tackle the food recognition problem. There are also some work for food industry. For example, [Russo et al. 2002] presented a system for monitoring the work of a fastfood employee using a single static camera and a video of an employee preparing a hamburger or sandwich is analyzed. Finally, the system produced a description of the sandwich that was prepared. Benefiting from the large-scale food data from social media, some works [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 typically addressed as a binary classification problem, where the algorithm is simply used to distinguish whether a given image is representing food or not, namely binary food detection [Kagaya et al. 2014; Ragusa et al. 2016]. Relevant works have considered either hand-crafted representations [Farinella et al. 2015a; Kitamura et al. 2009; Miyano et al. 2012] or deep representations [Anzawa et al. 2019; Kagaya and Aizawa 2015; Meyers et al. 2015]. Compared with hand-crafted features, an improvement is achieved via CNN based deep networks [Kagaya et al. 2014]. Numerous researchers have proposed CNN based models either for feature extraction [Aguilar et al. 2017a; Ragusa et al. 2016] or for the whole recognition process [Kagaya and Aizawa 2015; Singla et al. 2016]. For example, [Singla et al. 2016] reported the experiments on food/non-food classification using the GoogLeNet network. The best
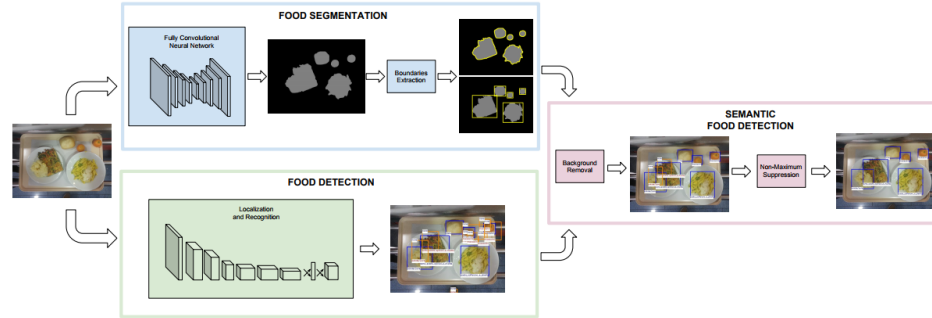
Fig. 6. The pipeline of semantic food detection [Aguilar et al. 2018]

performance obtained on the public datasets with more than 15,000 images have been reported in [Aguilar et al. 2017a] through the combination of the GoogLeNet for feature extraction, PCA for dimensionality reduction and SVM for classification. Different from binary food detection, [Bolanos and Radeva 2017] recently produced a food activation map on the input image for generating proposals of the bounding boxes and then used the GoogLeNet to recognize each of food types or food-related objects present in each bounding box. [Aguilar et al. 2018] fine-tuned the object detection algorithm YOLOv2 [Redmon et al. 2016] for food detection with multiple-food-items. Compared with food detection, food segmentation consists in classifying each pixel of the images representing a food. [Anthimopoulos et al. 2013] proposed a novel method for automatic segmentation and recognition of multi-food images, where each of the resulted segments is described by both color and texture features and classified by SVM. The latest research proposes an automatic weakly supervised method based on CNN [Shimoda and Yanai 2015] or distinct class-specific saliency maps [Shimoda and Yanai 2016], respectively. For example, [Shimoda and Yanai 2015] proposed a new region segmentation method via Region-CNN [Girshick et al. 2014] for food images with multiple food items.

As representative work, [Aguilar et al. 2018] proposed a semantic food detection framework (Figure 6), which consists of three parts, namely food segmentation, food detection and semantic food detection. Food segmentation uses the fully CNNs [Shelhamer et al. 2014] 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 object detection by combining results of segmentation and detection to obtain final food detection results.

Besides food recognition by food items, there are also some work on multi-label ingredient recognition. For example, Both [Chen et al. 2017d] and [Pan et al. 2017] used deep learning methods for automatic multi-class classification of food ingredients. [Bolanos et al. 2017] further proposed a method for multi-label ingredient prediction via the inception v3 and Resnet-50. [Zhang et al. 2016c] designed a multi-task learning framework with the embedded ingredient structure for multi-label ingredient recognition. [Zhang et al. 2016a] proposed a multi-task system that can identify dish types, food ingredients and cooking methods from food images with CNN. [Zhou and Lin 2016] proposed a novel approach to exploit rich ingredient and label relationships through bipartite-graph labels, and then combined bipartite-graph labels and CNN in a unified framework for multi-label ingredient recognition and dish recognition.

5.2.3 *Mobile Food Recognition.* The possibility of introducing smart multimedia applications in mobile environments is gaining more and more attention, due to the rapid spreading of smart portable devices. As a consequence, there is an
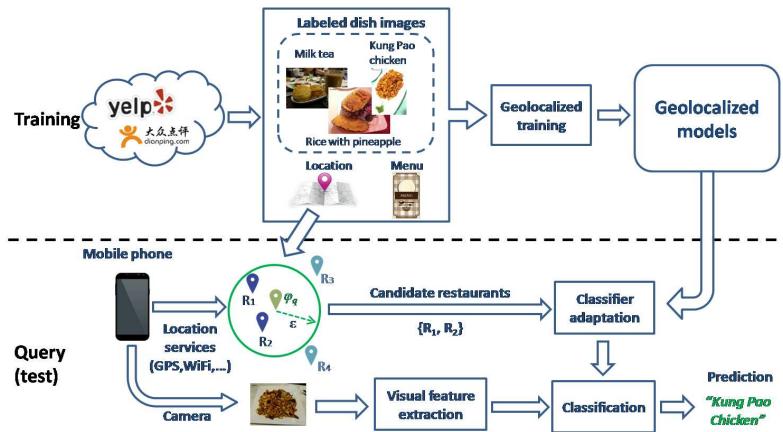
Fig. 7. The framework of restaurant-specific dish recognition [Xu et al. 2015]

increasing interest on applying food recognition to mobile environment to enable mobile food recognition. This also has other advantages of combined built-in inertial sensors with visual food recognition to jointly monitor activities of daily living, thus providing detailed information for the dietary assessments and management [Pouladzadeh et al. 2016a]. [Zhu et al. 2011] developed a method to identify food items using a single image acquired from the mobile device. They firstly automatically determined regions in an image where a particular food is located and then identified the food type based on its features including the color and texture features. [Kong and Tan 2011] proposed a camera phone based application DietCam, which considers food appearance from multiple perspectives for food recognition. [Oliveira et al. 2014] presented a semi-automatic system to recognize prepared meals which is lightweight and can be easily embedded on a camera-equipped mobile device. [Ravl et al. 2015] proposed a real-time food recognition platform combined with daily activities and energy expenditure estimation. [Kawano and Yanai 2015] proposed a mobile food recognition system FoodCam to enable real-time food image recognition on a smartphone. Deep learning offers a powerful tool to automatically produce high-level representation of complex multimedia data. Therefore, many deep learning networks, such as DenseNet [Huang et al. 2017], MobileNets [Howard et al. 2017] and ShuffleNets [Zhang et al. 2017b] have been proposed to adapt to the mobile devices. Therefore, deep learning based mobile food recognition methods have been fast developed. For example, [Tanno et al. 2016] extended FoodCam to DeepFoodCam by introducing the deep learning network for visual feature extraction. [Pouladzadeh and Shirmohammadi 2017] proposed a mobile food recognition system that can recognize multiple food items in one meal, such as steak and potatoes on the same plate to further estimate the calorie and nutrition of the meal.

5.2.4 *Restaurant-specific food recognition.* Besides mobile food recognition, there are some recent surveys indicating that more people from many countries opt to dine out, rather than at home[12]. Therefore, more and more works focus on the restaurant scenario for restaurant-specific food recognition. In this scenario, additional information such as the location and menu information is utilized. For example, [Bettadapura et al. 2015] presented a method for automatically recognizing food in restaurants leveraging location sensor data and various hand-crafted visual features. [Xu et al. 2015] proposed a framework incorporating discriminative classification in geolocalized settings and introduced the concept of geolocalized models, where DeCAF deep features and restaurant location information are utilized. As shown

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[12]http://www.whig.com/20171204/more-americans-opt-to-dine-out-rather-than-at-home#

in Figure 7, they first constructed a database of restaurants including geographical locations and menus and food images of corresponding dishes. Then, the geolocalized models are trained with these dish images, where each model is related to a particular geolocation. During the test time, the particular geolocation of the query defines a neighborhood with some candidate restaurants. For each query, corresponding geolocalized models are selected and combined into a new classifier adapted to the query. In addition, [Herranz et al. 2017, 2015] proposed a probabilistic graph model to connect dishes, restaurants and locations for food recognition. [Wang et al. 2016] proposed a multi-task convolutional neural network for simultaneous dish and restaurant recognition from food images. [Aguilar et al. 2018] conducted automatic food tray analysis in canteens and restaurants by food detection and segmentation based on CNNs for smart restaurants. [Bolaños et al. 2018] combined CNNs and Recurrent Neural Networks (RNNs) to determine its correct menu item corresponding to the restaurant given an image as the input.

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

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
[Hoashi et al. 2010]	SIFT,Color Texture, HoG	-	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

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
[Simonyan and Zisserman 2014]	VGG	-	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
[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

5.3 Retrieval

These massive amounts of data shared on various sites allow gathering food-related data such as text recipes, images, videos and user preference. A food-relevant retrieval engine is necessary to obtain what we need. 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 foods are mixed and stirred. In this case, we can retrieve recipes based on the image query, namely cross-modal retrieval. There are other advantages of having recipes. For example, recipe recommendation will help users cook a particular dish

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**

what he wants. In addition, these recipes provide other rich information, e.g., ingredients, macronutrient composition and cooking methods, which can enable the estimation of food calorie and nutrition facts.

According to retrieval types, food-relevant retrieval consists of three types: visual food retrieval, recipe retrieval and cross-modal recipe-image retrieval. For food image retrieval, [Kitamura et al. 2009] proposed a FoodLog system, which can distinguish food images from other images to retrieve personal food images for food balance estimation 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. [Barlacchi et al. 2016] introduced a search engine for restaurant retrieval based on dishes a user would like to taste rather than using the name of food facilities or their general categories. [Farinella et al. 2016] conducted the food image retrieval by comparing the images through similarity measures, where the food images are represented as vectors through the combination of different types of features, such as SIFT and Bag of Textons. [Ciocca et al. 2017] adopted CNN-based features for food image retrieval. For the recipe retrieval, [Wang et al. 2008] investigated the underlying features of Chinese recipes. Based on workflow-like cooking procedures, they model recipes as graphs and further propose a novel similarity measurement based on the frequent patterns, and devise an effective filtering algorithm to support efficient on-line searching. Recently, [Chang et al. 2018] proposed an interactive system RecipeScape to analyze multiple recipes for one dish. They changed the recipe instruction into a tree-structure representation for recipe similarity calculation. [Xie et al. 2011] further jointly utilized various features such as cooking flow features, eating features and nutrition features to create a hybrid semantic item model for recipe search.

Besides food/recipe retrieval, there are some researches on cross-modal recipe-image retrieval. For example, [Chen and Ngo 2016] proposed a multi-task deep learning architecture for simultaneous ingredient and food recognition. The learnt visual features and semantic attributes of ingredients are then used for recipe retrieval given dish pictures. [Chen et al. 2017b] introduced a stacked attention network to learn joint space from images and recipes for cross-modal retrieval. [Chen et al. 2017a] exploited rich food attributes for cross-modal recipe retrieval. [Min et al. 2017a] utilized a multi-modal Deep Boltzmann Machine for recipe-image retrieval. [Salvador et al. 2017] developed a hybrid neural
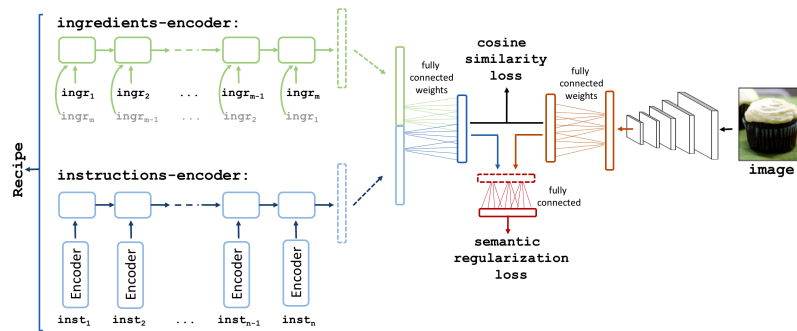
Fig. 8. The proposed im2recipe architecture for cross-modal recipe-image retrieval [Salvador et al. 2017]

network architecture, which jointly learned shared space via image and recipe embedding for cross-modal image-recipe retrieval, where visual features are learned by CNN while recipe features are learned by LSTM. [Micael et al. 2018] extended [Salvador et al. 2017] by providing a double-triplet strategy to jointly express both the retrieval loss and the classification one for cross-modal retrieval.[Wang et al. 2019; Zhu et al. 2019] further introduced adversarial networks to impose the modality alignment for cross-modal retrieval. [Salvador et al. 2019] proposed a new architecture for ingredient prediction that exploits co-dependencies among ingredients without imposing order for generating cooking instructions from an image and its ingredients.

As representative work, Figure 8 shows the proposed joint embedding model. There are mainly two components for a recipe: 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 the LSTM model 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 provides a summary of retrieval approaches with respect to features, dataset and tasks.

5.4 Recommendation

Food recommendation is an important domain for both individuals and society. Different from other types of recommendation system, 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 [Trattner and Elsweiler 2017a]. Taking all these factors into consideration, various recommendation methods are proposed. According to the recent survey [Trattner and Elsweiler 2017a], food recommendation consists of four types, namely content-based food recommendation [Freyne and Berkovsky 2010], collaborative filtering-based food recommendation, hybrid food recommendation [Ge et al. 2015a], context-aware food recommendation [Cheng et al. 2017; Zhang et al. 2016b] and health-aware food recommendation [Nitish et al. 2017][Achananuparp and Weber 2016; Schäfer et al. 2017; Trattner and Elsweiler 2017b; Yang et al. 2017].

For content-based food recommendation, recipe oriented recommendation has been extensively studied. For example, [Freyne and Berkovsky 2010] made recommendations by breaking recipes down into individual ingredients and scoring

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. 2017]	Food images	-	Food524DB	Food retrieval
[Micael et al. 2018]	Food images	Ingredients & Instructions	Recipe 1M	Cross-modal retrieval
[Wang et al. 2019]	Food images	Ingredients & Instructions	Recipe 1M	Cross-modal retrieval
[Zhu et al. 2019]	Food images	Ingredients & Instructions	Recipe 1M	Cross-modal retrieval
[Salvador et al. 2019]	Food images	Ingredients & Instructions	Recipe 1M	Cross-modal retrieval

based on the ingredients contained within recipes, which users had rated positively. In such methods, different methods for recipe based content representation are adopted, including topic model based representation [Kusmierczyk and Norvag 2016; Nedovic 2013], structure based representation [Jermsurawong and Habash 2015; Kiddon 2016] and multi-modal representation with various attributes [Min et al. 2018a, 2017b].

For collaborative filtering-based methods, classic Singular Value Decomposition (SVD) [Harvey et al. 2013] and Matrix Factorization (MF) [Ge et al. 2015a] have been used widely for recommendation. For example, [Ge et al. 2015a] utilized a MF approach for food recommender systems that fuses ratings information and user supplied tags to achieve significantly better prediction accuracy than content-based and standard matrix factorization baselines. In addition, other methods such as Latent Dirichlet Allocation and Weighted matrix factorization are also used for food recommendation [Trattner and Elsweiler 2017b].

For context-aware approaches, numerous exploratory data analysis have demonstrated that rich context such as gender, time, hobbies, location and cultural aspects is important in food recommendation. For example, [Cheng et al. 2017] conducted context-aware food recommenders, which are created by filtering users and items according to relevant context factors. In addition, exploring other factors such as the culinary cultures can also help for context-aware food recommendation. For example, [Ahn et al. 2011] constructed a data-driven flavor network relating ingredients to discover the patterns of ingredient combinations. [Golder and Macy 2011] has discovered clear, universal rhythmic

patterns regarding work, sleep and eating from millions of public Twitter messages. Similar temporal and spatial patterns can be found by analyzing online recipe websites [Wagner et al. 2014] [Kusmierczyk and Trattner 2015a]. [Silva et al. 2014] proposed a new method to identify cultural boundaries and similarities across populations at different scales based on the analysis of Foursquare check-ins. Such cultural analysis and understanding from recipes and social media can help us develop recommendation mechanisms considering the cultural characterization of specific urban areas. In addition, we can also discover user's food preference [Kusmierczyk and Trattner 2015b] for context-aware food recommendation.

Health-aware food recommendation is unique for food recommendation. Incorporating health into the recommendation has largely been a recent focus [Ge et al. 2015b; Markus et al. 2018; Nag et al. 2017b]. For example, [Ge et al. 2015b] incorporates nutritional aspects into the recommendation approach based on a so-called "calorie balance function". [Nag et al. 2017b] proposed a live personalized nutrition recommendation system, which can efficiently calculate which items are healthiest and re-rank and filter results to users based on their personalized health data streams and environmental context. Recently, [Markus et al. 2018] built a model using different kinds of features from a recipe's title, ingredient list and cooking directions, popularity indicators such as the number of ratings and the user comments and visual features to estimate the healthiness of recipes for health-aware recipe recommendation. [Thanh and Gatica-Perez 2017] proposed a method for analyzing food and drink consumption patterns on Instagram.

In addition, [Maruyama et al. 2012] proposed a mobile recommendation system, which recognized food ingredients and recommended recipes related to these recognized ingredients to users in a real-time way. [Fadhil 2018] addressed some challenges of chatbot application for meal recommendation. [Phanich et al. 2010] proposed a food recommendation system for diabetic patients using food clustering analysis to recommend proper substituted foods in the context of nutrition and food characteristic. [Rehman et al. 2017] used the ant colony algorithm to generate optimal food list and recommended suitable foods for patients based on users' pathological reports. Several studies in the field of nutrition science have shown that proper nutrition and health labels help people to make better food choices [Elbel et al. 2011; Sonnenberg et al. 2013]. There are also some works for restaurant recommendation [Zhang et al. 2016b] or food truck recommendation [Rivolli et al. 2017]. Besides the above-mentioned references, we refer readers to one recent survey of food recommendation in [Theodoridis et al. 2019; Trattner and Elsweiler 2017a].

5.5   Prediction and Monitoring

Online social networks (e.g., Twitter, Instagram and Facebook) with billions of users and shared large-scale food data, have become rich sources to conduct food-related prediction and monitoring. Prediction and monitoring from the social media can provide various health-relevant information to enable further decision, such as predicting recipe popularity [Sanjo and Katsurai 2017], the national obesity, diabetes statistics [Abbar et al. 2015] and monitoring the public health [Capurro et al. 2014].

Food-related prediction in social media has gained more attention [Abbar et al. 2015; Kusmierczyk and Trattner 2015b; Wagner et al. 2014; West et al. 2013]. For instance, [Ma et al. 2015] predicted the income from the preference for spicy foods. [Mejova et al. 2015] analyzed large scale images on Instagram to study food consumption patterns from the Unite States. [Abbar et al. 2015] used daily tweets of users about food from Twitter to predict the national obesity and diabetes statistics. [Fried et al. 2014] collected a large corpus of food-related tweets from Twitter and used them to predict latent population characteristics such as geographic location of authors, overweight and diabetes rates. [De Choudhury et al. 2016] proposed a simple ingredient matching method to estimate nutritional properties of food posts on Instagram, making use of the USDA National Nutrient Database for the matching process. [Sanjo

and Katsurai 2017] predicted the recipe popularity by fusing their multimodal features including visual and semantic features extracted from the deep network. In addition, some work such as [Kusmierczyk and Trattner 2016] predicted online food production patterns from online food community.

Recently, using the social media for monitoring public health has received more attention [Capurro et al. 2014]. In the early years, in order to conduct large-scale dietary studies, we should use questionnaires and food diaries to keep track of participants' daily activities, which can be inaccurate and expensive. Alternatively, social media such as Twitter and Instagram provides its users with a way of recording their daily lives, such as dietary choices. Some studies have adopted data-driven approaches to analyze the food consumption on massive scale from these records in the social media [Culotta 2014; Ofli et al. 2017; Silva et al. 2014]. For example, [Mejova et al. 2016] exploited 10 million posts from 1.7 million users on Instagram to capture global use of the popular #foodporn hashtag. [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] presented a new method to detect personal health mentions in Twitter.

6 CHALLENGES

Food computing has received more and 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, many food dishes have deformable food appearance and are thus lack of rigid structures. Ingredients can be the constituent part of food. However, ingredients from many 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 many 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 and 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. Many types of food images do not 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. Many 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 many 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 many 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 [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 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 fast developed in many 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[13]. 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, [Ofli et al. 2017] utilized large-scale food images from Instagram to study the food perception problem. [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   Food Log-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, food logs records users' eating history with multimodal signals, With the economic growth of the world, more and more people resorts to food

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

logs for recording their general diet via the smartphone. Food log-oriented food computing will become more and more important for its multifarious applications. (1) Food logs are most critical for health. Some works [Waki et al. 2015], [Kitamura et al. 2008] [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[14], 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 food log oriented food recognition is also needed. (2) Food logs record what one eats or drinks daily and thus reflect their eating habits. Therefore, mining and analyzing rich food log data will enable personalized food recommendation, which can offer healthier options for health-aware food recommendation [Trattner et al. 2017]. In addition, food logs record current popular food. We can aggregate the food log 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 many vertical fields. For example, food computing can enable many 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 has a profound impact on many aspects of human, such as the survival, identity, religion and culture. Food computing can connect food and human to improve human health, understand human behaviors and culture. The massive amount of food-related data from various sources and the advances in computer science and other principles (e.g., neuroscience and cognitive science) have provided us with unprecedented opportunities to tackle many food-related issues via food computing. In this survey, we provide an extensive review of the most notable works to date on the datasets, tasks and applications of food computing, from food-oriented data acquisition and analysis, perception, recognition, retrieval, recommendation, prediction and monitoring to its various applications and services. This survey discusses some key challenges in food computing including robust and accurate food image recognition,vision based dietary management system, multiple-network oriented food data fusion and mining, health-aware personalized food recommendation and its applications for food science. Finally, this survey suggested some research directions, such as large-scale standard food dataset construction, large-scale robust food recognition system, joint deep and broad learning for food computing, food-oriented multimodal knowledge graph construction and inference, food computing for food logs and other emerging vertical fields. These lines of promising directions need further research.

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

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