OnionBot: A System for Collaborative Computational Cooking

Bennet Cobley  
Imperial College London  
bennet.cobley16@imperial.ac.uk

David Boyle  
Imperial College London  
david.boyle@imperial.ac.uk

Figure 1: (a) Collaborative computational cooking. The system combines manual and automatic cooking assistance: (b) automatic management of heating tasks; (c) intelligent reminders and warnings; (d) on-screen instructions for the user to execute.

ABSTRACT
An unsolved challenge in cooking automation is designing for shared kitchen workspaces. In particular, robots struggle with dexterity in the unstructured and dynamic kitchen environment. We propose that human-machine collaboration can be achieved without robotic manipulation. We describe a novel system design using computer vision to inform intelligent cooking interventions. This human-centered approach does not require actuators and promotes dynamic, natural collaboration. We show that automation that assists user-led actions can offer meaningful cooking assistance and can generate the image databases needed for fully autonomous robotic systems of the future. We provide an open source implementation of our work\(^1\) and encourage the research community to build upon it.

CCS CONCEPTS
• Human-centered computing → Interaction devices; • Computer systems organization → Robotics.

KEYWORDS
computational cooking, cobots, computer vision, human-computer interaction

1 INTRODUCTION
Automation devices have become an essential part of the home. Appliances that optimize specific functions take on repetitive cooking and cleaning tasks, bringing efficiency and convenience to domestic life. With the rapid development in ubiquitous computing and computer vision, we foresee that appliances will further assist with creative roles, including in the kitchen; computational cooking will bring a new generation of partnership with food technology.

Studies typically explore high degree-of-freedom robot arms as solutions for automated cooking [5, 11, 14, 16, 28, 29]. Robot arms mimic general human-kitchen interaction, but the dynamic and unstructured kitchen environment poses significant manipulation challenges. Consequently, most solutions compromise in a static, human-free workspace [5, 11, 14, 16, 28, 29].

Coexistence in a shared environment is critical to feasibility of next-generation systems. Collaborative robots leverage human-robot interaction in shared workspaces, combining the best of human adaptability and robot repeatability [9]. In Cooking with Robots, Sugiura et al. proposed collaborative mobile counter-top robots to assist with stove cooking. They found that collaboration is more practically feasible and encourages more natural human-robot interactions, but reported manipulation limitations [24]. In the decade since, few collaborative cooking breakthroughs have been reported.

This paper presents a new approach to the collaborative cooking problem. To achieve feasibility in a dynamic environment, we propose that the system should instead take a more passive role, assisting user-led actions rather than replacing the chef. Removing the robot arm avoids manipulation challenges with currently available technology. We instead leverage computer vision techniques to inform contextual instructions for the user to execute (Figure 1). We introduce a system that balances manual manipulation with automatic heat control, promoting natural and dynamic interactions. Our main contributions include:

• A first-of-its-type human-centered approach to computational cooking.
• A novel system for recipe image collection, training, and application of computer vision.
• An open source implementation of the hardware and software, to enable the community to build image datasets and accelerate progress by developing ideas in the open.

\(^1\)An open source implementation of OnionBot is available at github.com/onionbot.
This system is proposed as a key enabling technology on the critical path to fully autonomous (non-passive) systems of the future.

2 RELATED WORK

2.1 Cooking Robotics
The semi-structured kitchen environment poses interesting challenges for robotics research — perception in cluttered environments, object manipulation, and complex cooking actions — while allowing for simplification due to consistency of kitchen spaces, tools, tasks, and recipe structure [5]. Recipe websites have been parsed into low-level action sequences [5, 14]. Cooking videos on YouTube have been used to automatically learn and execute action sequences [30].

High degree-of-freedom robot arms [5, 14, 16] and humanoid robots [11, 28, 29] are typically used to mimic human-kitchen interaction in robotics research. Such studies do not allow for shared human-robot workspaces, limiting the real-world usefulness of the methods. Moley [2] motion-captures and replicates recipes demonstrated by a user, but cannot collaborate on the cooking process. In Cooking with Robots, Sugiura et al. proposed Cooky, a human-in-the-loop stove-top cooking system with mobile robots. Cooky predates modern computer vision techniques, so users must attach visual markers (paper tags) to utensils and ingredients before before cooking [24]. The robots allow for collaboration in a shared workspace but only provide rudimentary cooking capabilities.

2.2 Digital Kitchen Interfaces
Tablets and other screens are an increasingly important component of the kitchen. Voice assistance has been used to reduce the need to use screens with dirty hands [17]. Julia is a commercially available device that combines various preparation and cooking functions with a tablet interface and voice assistant [3]. With ChopTop, Celik explores an interactive chopping board that combines simplified on-screen recipe instructions with weighing and timing functionality for inexperienced cooks [6]. Augmented Reality has been explored as a solution for displaying guidance based on actions in the kitchen [7, 21]. The complementary aspects of the above interfaces could feasibly be integrated into a collaborative computational cooking system, benefiting from supplementary information from computer vision.

2.3 Computer Vision
Food images have many complex features that are challenging to define, posing significant computational challenges to conventional image based decision making approaches [20]. Deep learning has outperformed manual feature extraction and conventional machine learning techniques in food quality analysis [31]. Deep learning has been used in food classification, quality detection, calorie estimation and food contamination investigation [4, 8, 31].

A large training dataset is critical to food image recognition as it enables learning of general features, reducing the effects of overfitting [20]. NutriNet [20] introduces an architecture trained on 220,000 images gathered using Google Images searches of food and drink items. While 94.5% top-five accuracy was achieved on the testing subset, top-five accuracy for real-world images was 55%.

The authors cite noise, occlusion, and overfitting to the Google Images dataset (Figure 2) as possible causes [20].

Figure 2: NutriNet Dataset: Real-world smartphone images differ significantly in style and composition to training images scraped from Google Images, causing accuracy losses. Adapted from [20].

The Recipe1M [22] and Recipe1M+ [19] datasets include 1 million internet recipes and their corresponding completed dish images. The Cookpad dataset [12] (1.6 million images and recipes) also includes 3.1 million cooking process images collected by the Cookpad recipe app. Ingredient state is important to determining subsequently performed actions (whether a tomato is whole, sliced, or diced for example). A food state classifier was trained to identify 11 different states for 17 ingredients [15]. The available datasets either include images upon recipe completion or at a few key points. Images captured at regular time intervals throughout the entire cooking process may be useful for process control. To the best of our knowledge, no ‘continuous cooking process datasets’ have been established.

MISO Robotics have developed a device that combines a camera with a far-infrared thermal sensor data to assist grilling and frying tasks [23, 32]. The MISO AI computer vision model tracks burger cooking progress, increasing operator efficiency and reducing failure rates [1].

3 PROPOSED ARCHITECTURE
Desirable characteristics for a collaborative cooking system are as follows:

1. **Dynamic**: The system should operate in a human-centric workspace and adapt to interventions from the chef. Fast responses to interventions should be a characteristic of the system; frame rate will ideally be maximized and latency minimised.

2. **Small**: Ensuring the system fits comfortably on a kitchen counter is a rational approach.

3. **Accurate**: The system should detect and control cooking temperature to an approximately human level.

4. **Robust**: Food computer vision attempts in the literature have reported limited real-world success. Perception robustness is desired; training on visually consistent in-context images should aid model accuracy.

Desirable characteristics motivated by the need for large image datasets are as follows:

5. **Automated labelling**: Suitable cooking process image sets do not exist in the literature; an interface should facilitate...
easy, real-time image labelling. Researchers should be able to generate training sets for their own use cases (recipes).

(6) Open source: An open source community could crowd-source labelled images and share recipe models. The system should utilise off-the-shelf and 3D-printed components.

(7) Accessible: The system should simplify the model training process, making it accessible to cross-disciplinary researchers without machine learning expertise. An API should facilitate development of further functionality.

Figure 3 shows an overview of our system. We add sensing and control functionality to a commercially available induction cooker. Researchers can use the Control Panel and Real-time Labelling interface (Section 4.4) for development, and a chef would use the ‘Sous chef’ assistant interface while cooking. The following section describes the implementation of our new system designed to satisfy the above design considerations.

4 IMPLEMENTATION

4.1 Sensing

A 120° wide-angle lens enables camera placement close to the pan to optimize overall height (Figure 4). Image classification is performed on the edge (on device); initial testing suggested that inferencing would slow frame rate, so a Google Coral AI USB Accelerator (Tensor Processing Unit) improves performance. We use a MLX90640 Far-Infrared Sensor Array to measure pan temperature, an established method in the literature [23, 26]. Components are housed in a 3D-printed PLA enclosure, for which 3D files are publicly available.

4.2 Control

We use a Buffalo 3000W Induction Cooker, controlled by a front-mounted servo motor. A Parallax Feedback 360° Servo provides appropriate range of motion and returns angular position with an internal Hall effect sensor. We use a PID controller to manage temperature, as established in the literature [25]. A Raspberry Pi Foundation 7” Touchscreen display provides instructions, reminders and warnings. While actuation is limited to induction power control, the human-machine-interface provides a powerful secondary control method that leverages the dexterity and flexibility of the human as an actuator.

Recipes are programmed following the finite state machine format presented in Figure 5. This example shows a variety of unique assistive functionality enabled by image classification techniques and temperature control. For this simple pasta boiling example, the device can:

- Automatically advance through recipe instructions; no need to interact with a screen with messy hands.
- Automatically switch off the power on pan removal, then switch it back on on pan return.
- Hold the pan at a particular temperature in degrees.
- Automatically start a timer for a recipe instruction, then turn off the heat when the timer is complete.
- Show a reminder when the pan has not been stirred for a duration, then hide the warning when the pan is stirred.
- Show a warning if the pan boils over, and turn down the heat.

These functions aim to reduce the cognitive load on the chef, allowing their attention to be focused on the more creative aspects of cooking. We hope that by facilitating perfect execution of recipes every time we will enable convenience, waste-reduction, cost, and health benefits for users of all ability levels.

4.3 Computer Vision

The unstructured kitchen workspace is a challenging environment for computer vision [5]. We propose a fixed field-of-view including only the stovetop, creating a more structured environment to improve perception robustness. Fixed LED lighting above the pan further improves image consistency.

The hot pan creates tough conditions for the camera and thermal array. Initial testing revealed that image quality was deteriorated due to condensation on the sensors. We developed a mechanism using a Sunon 12V DC Brushless Blower to flow a layer of dry air over the sensors to minimise condensation and temperature variation.

Studies have shown poor real-world results in training general food-classification and general food-state-classification models [15, 18, 20]. However, cooking image classification can be simplified by training individual models for individual recipes. We realized that we only need to identify key events at which actions are to be performed. We establish a milestone-based approach, shown in Figure 7. We classify key events for a single recipe, dramatically simplifying the classification problem. For example, we do not attempt to learn the features of an onion in any context; we only differentiate the ‘Onions added to the pan’ milestone from the ‘Onions cooked until soft’ milestone, so the appropriate action may be taken at each step.

4.4 Image Labelling

Suitable milestone-based image datasets do not exist in the literature, so it is necessary for the system to self-generate data for each recipe. We designed a web interface (Figure 6) for labelling images in real-time while cooking. Using the Control Panel, researchers can monitor and control all elements of the system. Labelled images are continuously uploaded to Google Cloud at 0.5 second intervals, and a database of labels is automatically created, formatted for import into AutoML.

We generated image datasets for the pasta and tomato sauce test recipes (from Figures 5 and 7) using the system. We initially found that classes were unbalanced due to variation in milestone duration, so slower milestones were undersampled to balance classes. Over 5 cooking sessions we captured 2,045 images across 4 milestones for pasta, and 4,042 images across 6 milestones for tomato sauce.

4.5 Model Training

To simplify the model training process for cross-disciplinary researchers, we take advantage of Google’s AutoML automated training service. Google does not disclose architecture information, but we speculate that training is based on established architectures such as ResNet [13], likely alongside transfer learning techniques [27].

Unlike scraped [18–20, 22] or crowd-sourced [12] datasets in the literature, our training images are captured on-device. As such,
we should not expect overfitting to training data due to contextual information such as style and composition. However, we did find that models will associate stirring utensils with a particular milestone (always stirring onions with a wooden spoon, for example, causes confusion when a wooden spoon appears in a different milestone). As such, we added more examples of contextual noise to all classes of the training data, including variation in pans, lighting, and stirring utensils. Models were trained using Google AutoML until performance no longer improved (typically 1-2 node-hours).

At 0.5 confidence threshold, AutoML achieved 100% test set precision for pasta milestone classification and 99.5% test set precision for tomato sauce milestone classification. The confidence threshold was also set at 0.5 for real-world testing, with iterations performed until each milestone triggered at the correct time.

5 EXPERIMENTAL VALIDATION

The full system has been shown to work consistently. We performed preliminary tests with a student in our lab with no knowledge of the system. The student must cook pasta and tomato sauce following the on-screen instructions exactly. This simple recipe requires the system to successfully demonstrate 9 classifier-informed 'proceed to next step' events, 3 time-based events, and 3 classifier-informed 'warning' interventions. The most challenging vision task is detecting when frying onions become soft. The test is failed if the system advances too early or late, so the skip-forward, skip-back or cancel-warning buttons are pressed. The system was shown to work repeatably over 10 initial tests of approximately 30 minutes each, and the test user was able to reproduce these results.

6 OPEN SOURCE COLLABORATIVE COMPUTATIONAL COOKING

We present here key enabling components for collaborative computational cooking; outlining feasible approaches to connected
systems and computer vision methods. The critical remaining component is data. Food brings people together; we hope that an open-source computational cooking movement could inspire a community to build their own systems. A first-of-its-kind ‘continuous cooking process database’ could be crowd-sourced, with users labelling and sharing their images and recipes. Metadata captured by the system is also incredibly rich: recipes, temperatures, ingredients, and corrective human inputs are recorded. A large, rich image dataset would enable new, advanced research with deep learning.

We open source our work in aid of accelerating research progress by developing in the open. We provide an implementation of our system including: CAD files, bill of materials (BOM), real-time labelling interface, device control panel interface, and ‘sous chef’ touchscreen interface. The required components, excluding the 3D-printed enclosure, are available off-the-shelf for under $500.

7 DISCUSSION AND LIMITATIONS

The test user successfully cooked a meal with the system, demonstrating 9 successful semi-autonomous interventions. Our user-led assistance approach to cooking automation allowed the system to operate in the dynamic kitchen environment. This shows obvious size and feasibility advantages over previous solutions using robot arms in static-only environments [5, 11, 14, 16, 28, 29]. Incremental BOM cost for an appliance manufacturer incorporating this technology into an existing product would be a fraction of the cost of any robot arm.

However, end users may expect a more autonomous system; we require users to execute many cooking actions themselves. Notwithstanding, we believe that the value of the system is instead demonstrated by its capability to reduce cognitive load on the chef by acting as a ‘second pair of eyes’. We argue that intelligent screen-based guidance can provide meaningful assistance and encourages more natural human-robot collaboration. We have not yet established whether the system can add value for more complex recipes, which we see an opportunity for future work.

Vision system responsiveness depends on frame rate. We found that our 2 Hz frame rate gives an instantaneous event response time of approximately 2 seconds (propagation time for the rolling average filter). Response time to more gradual changes depends on confidence. Future work will improve responsiveness through frame rate optimisations.

PID control proved to be an adequately accurate temperature control method. We do not explore how descriptive vision outputs such as ‘pasta is boiling over’ should feed into precise PID control systems. Future work could explore Fuzzy Logic Control Systems as an alternative. Fuzzy logic, also used in the food industry, mimics human reasoning in allowing computers to behave imprecisely, enabling descriptive inputs to control precise systems [8].

For computer vision robustness, examples of variation and noise must be manually introduced to every class of training data for each recipe. This is a laborious process. Future work may explore Transfer Learning, where knowledge gained from solving one problem is applied to new problems [10]. Robustness information such as ‘ignore features that look like hands’ could be transferred so that examples are not necessary in new training sets.

Images were successfully labelled in real-time using our control and labelling software. A limitation of the ‘milestones’ classification approach is that individual models must be trained for any new recipe. However, in future this process could be automated.

Recipes must be manually encoded into sequences of functions corresponding to trained models. Studies have explored automatic parsing of recipe websites into low-level action sequences [5, 14].

---

Figure 5: An example Finite State Machine for boiling pasta. The ‘sous-chef’ interface displays recipe guidance (shown) according to pan conditions. This simple recipe can be followed in its entirety without touching a screen.
Figure 6: The Control Panel interface for researchers connects to the API. It includes: (a) parameter adjustment, (b) thermal array live stream, (c) camera live stream, (d) time series temperature plot, (e) real-time labelling controls, (f) image set information, (g) image inference information.

Our recipe sequencing structure could feasibly be generated by Natural Language Processing techniques in the literature [10].

To the best of our knowledge, ‘continuous cooking process datasets’ have not yet been established in the literature. Networked devices with basic functionality could incentivize users to start sharing labelled images and recipes. A large, rich, crowd-sourced cooking dataset could facilitate development of advanced deep learning models, with new functionality available as over-the-air updates.

8 CONCLUSION

This paper proposes a novel system for assisted cooking in dynamic environments. We show technical feasibility for our system, confirming that it can successfully assist a test user in executing a simple meal. The system uses computer vision techniques and temperature control to provide intelligent and natural interventions during stove-top cooking. Users cook with the support of instructions and guidance from the digital Sous Chef. We argue that computational cooking systems should take predominantly passive roles until challenges with current robots in dynamic workspaces are overcome. In the meantime, these assistive devices should build image databases and refine vision models for future automation. Finally, we emphasize that large recipe image datasets will be critical to any cooking automation system. We hope that developing systems and datasets in the open will accelerate the progress of computational cooking. We provide an open source implementation of our work to encourage future research.
REFERENCES

[1] 2020. MISO AI. https://misorobotics.com/miso-ai/ Accessed May 2020.

[2] 2020. The World’s First Robot Kitchen. https://www.moley.com/ Accessed September 2020.

[3] 2020. Welcome to CookingPal. https://www.cookingpal.com/ Accessed September 2020.

[4] Madhukar Bhotmange and Pratima Shastri. 2011. Application of artificial neural networks to food and fermentation technology. Artificial neural networks-industrial and control engineering applications. Croatia: InTech (2011), 201–222.

[5] Mario Bollini, Stefanie Trillex, Tyler Thompson, Nicholas Roy, and Daniela Rus. 2013. Interpreting and executing recipes with a cooking robot. In Experimental Robotics. Springer, 481–495.

[6] Tuana Celik, Orsolya Lukacs-Kisbandi, Simon Partridge, Ross Gardiner, Gavin Parker, and Peter Bennett. 2018. Choptop: An Interactive Chopping Board. In Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems. 1–6.

[7] JD’Agostini, I Bonetti, A Salem, L Passerini, G Fiacco, P Lavanda, E Motti, Michele Stocco, KT Gashay, EG Abebe, et al. 2018. An augmented reality virtual assistant to help mild cognitive impaired users in cooking a system able to recognize the user status and personalize the support. In 2018 Workshop on Metrology for Industry 4.0 and IoT. IEEE, 12–17.

[8] Peter John Fellows. 2009. Food processing technology: principles and practice. Elsevier.

[9] R Brent Gillaspie, J Edward Colgate, and Michael A Peshkin. 2001. A general framework for cobot control. IEEE Transactions on Robotics and Automation 17, 4 (2001), 391–401.

[10] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. 2016. Deep learning. MIT press.

[11] Fabien Gravot, Atsushi Haneda, Kei Okada, and Masayuki Inaba. 2006. Cooking for humanoid robot, a task that needs symbolic and geometric reasonings. In Proceedings 2006 IEEE International Conference on Robotics and Automation. 2006. ICRA 2006. IEEE, 462–467.

[12] Jun Harashima, Sachiko Nakagawa, and Masahiko Narita. 2017. Cooking assistant for humanoid robot. In Robot Learning and Execution of Robotic Cooking Using Batch Bayesian Optimization. IEEE Robotics and Automation Letters 5, 2 (April 2020), 760–765.

[13] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual networks to food and fermentation technology. Artificial neural networks-industrial and control engineering applications. Croatia: InTech (2011), 201–222.

[14] Kai Junge, Josie Hughes, Thomas G. Thuruthel, and Fumiya Iida. 2020. Improving Robotic Cooking Using Batch Bayesian Optimization. IEEE Robotics and Automation Letters 5, 2 (Apr 2020), 760–765.

[15] Madhukar Bhotmange and Pratima Shastri. 2011. Application of artificial neural networks to food and fermentation technology. Artificial neural networks-industrial and control engineering applications. Croatia: InTech (2011), 201–222.

[16] Mario Bollini, Stefanie Trillex, Tyler Thompson, Nicholas Roy, and Daniela Rus. 2013. Interpreting and executing recipes with a cooking robot. In Experimental Robotics. Springer, 481–495.

[17] Seisichi Kumagai, Tomoko Sato, Hiroshi Sano, Hiroshi Tauchi, Norio Maeda, Yuki Horiguchi, Sachiko Nakagawa, and Masahiko Narita. 2017. Cooking assistant service utilizing an interactive robot. In 2017 IEEE/SICE International Symposium on System Integration (SII). IEEE, 986–991.

[18] Chang Liu, Yu Cao, Yan Luo, Guanling Chen, Vinod Vokkarane, and Yunshe Ma. 2016. Deepfood. Deep learning-based food image recognition for computer-aided dietary assessment. In International Conference on Smart Homes and Health Telematics. Springer, 37–48.

[19] Javier Marin, Aritro Biswas, Ferda Olli, Nicholas Hynes, Amaa Salvador, Yusuf Aytar, Ingmar Weber, and Antonio Torralba. 2019. Recipe1m+: A dataset for learning cross-modal embeddings for cooking recipes and food images. IEEE transactions on pattern analysis and machine intelligence (2019).

[20] Simon Mezgec and Mattusoo Sano. 2008. A virtual agent for cooking navi-gation system using augmented reality. In International Workshop on Intelligent Virtual Agents. Springer, 97–103.

[21] Immermann Addressing Industrial and Consumer Needs for Food Processing. Germany: Elsevier.

[22] Ahmad Babaeian Jelodar, Md Sirajus Salekin, and Yu Sun. 2018. Identifying object states in cooking-related images. arXiv preprint arXiv:1805.06956 (2018).

[23] Antonio Visioli. 2006. Learning cross-modal embeddings for cooking recipes and food images. In Proceedings of the IEEE conference on computer vision and pattern recognition. 3020–3028.

[24] Ryan W Sinnet, Robert Anderson, Zachary Zweig Vinegar, William West, David Zito, and Sean Olson. 2018. Multi-sensor array including an ir camera as part of an automated kitchen assistant system for recognizing and preparing food and related methods. US Patent App. 16/100,889.

[25] Yuta Sugitani, Daisuke Sakamoto, Anusha Withana, Masahiko Inami, and Takeo Igarashi. 2010. Cooking with robots: designing a household system working in open environments. In Proceedings of the SIGCHI conference on human factors in computing systems. 2427–2430.

[26] Antonio Visioli. 2006. Practical PID control. Springer Science & Business Media.

[27] Michael Vollmer and Klaus-Peter Möllmann. 2017. Infrared thermal imaging: fundamentals, research and applications. John Wiley & Sons.

[28] Catherine Wong, Neil Houlsby, Yifeng Lu, and Andrea Gesmundo. 2018. Transfer learning with neural automl. In Advances in Neural Information Processing Systems. 8356–8365.

[29] Christian Friedl, Christian Friedl, Christian Friedl, Christian Friedl, and Christian Friedl. 2018. Llama: A robotics framework for cobot control. IEEE Transactions on Robotics (2019).

[30] Ryan W Sinnet, Robert Anderson, Zachary Zweig Vinegar, William West, David Zito, and Sean Olson. 2018. Multi-sensor array including an ir camera as part of an automated kitchen assistant system for recognizing and preparing food and related methods. US Patent App. 16/100,889.

[31] Yuta Sugitani, Daisuke Sakamoto, Anusha Withana, Masahiko Inami, and Takeo Igarashi. 2010. Cooking with robots: designing a household system working in open environments. In Proceedings of the SIGCHI conference on human factors in computing systems. 2427–2430.

[32] Antonio Visioli. 2006. Practical PID control. Springer Science & Business Media.

[33] Michael Vollmer and Klaus-Peter Möllmann. 2017. Infrared thermal imaging: fundamentals, research and applications. John Wiley & Sons.

[34] Catherine Wong, Neil Houlsby, Yifeng Lu, and Andrea Gesmundo. 2018. Transfer learning with neural automl. In Advances in Neural Information Processing Systems. 8356–8365.

[35] June-sup Yi, Min Sung Ahn, Hosik Chae, Hyunwoo Nam, Donghun Noh, Dennis Hong, and Hyunggil Moon. 2020. Task Planning with Mixed-Integer Programming for Multiple Cooking Task Using dual-arm Robot. In 2020 17th International Conference on Ubiquitous Robots (UR) (IEEE), 29–35.

[36] Jiaxin Zhai, Weixin Yan, Zhuang Fu, and Yanzheng Zhao. 2012. Kinematic analysis of a dual-arm humanoid cooking robot. In 2012 IEEE International Conference on Mechatronics and Automation. IEEE, 249–254.

[37] Heja Zhang and Stefanos Nikolaidis. 2019. Robot Learning and Execution of Collaborative Manipulation Plans from YouTube Cooking Videos. arXiv (2019), arXiv–1911.

[38] Lei Zhou, Chu Zhang, Fei Liu, Zhengjun Qiu, and Yong He. 2019. Application of deep learning in food and drink image recognition system for dietary assessment. Nutrients 9, 7 (2017), 657.

[39] June-sup Yi, Min Sung Ahn, Hosik Chae, Hyunwoo Nam, Donghun Noh, Dennis Hong, and Hyunggil Moon. 2020. Task Planning with Mixed-Integer Programming for Multiple Cooking Task Using dual-arm Robot. In 2020 17th International Conference on Ubiquitous Robots (UR) (IEEE), 29–35.

[40] Jiaxin Zhai, Weixin Yan, Zhuang Fu, and Yanzheng Zhao. 2012. Kinematic analysis of a dual-arm humanoid cooking robot. In 2012 IEEE International Conference on Mechatronics and Automation. IEEE, 249–254.

[41] Heja Zhang and Stefanos Nikolaidis. 2019. Robot Learning and Execution of Collaborative Manipulation Plans from YouTube Cooking Videos. arXiv (2019), arXiv–1911.

[42] Lei Zhou, Chu Zhang, Fei Liu, Zhengjun Qiu, and Yong He. 2019. Application of deep learning in food and drink image recognition system for dietary assessment. Nutrients 9, 7 (2017), 657.

[43] June-sup Yi, Min Sung Ahn, Hosik Chae, Hyunwoo Nam, Donghun Noh, Dennis Hong, and Hyunggil Moon. 2020. Task Planning with Mixed-Integer Programming for Multiple Cooking Task Using dual-arm Robot. In 2020 17th International Conference on Ubiquitous Robots (UR) (IEEE), 29–35.