A Quick Overview of Robot Cooking

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Abstract. Robotic cooking can alter both home and commercial kitchens by automating and improving a variety of cooking operations. The incorporation of modern technology, such as robot manipulation, computer vision, deep learning, modal sensors, and other machine learning techniques, allows these robots to perform difficult culinary operations with accuracy and consistency. However, several challenges still exist in adapting robotic systems to the diverse tools and techniques used in cooking. Robots need to use a wide array of kitchen tools designed for humans, such as knives, spatulas, and whisks. This requires not only the ability to grasp and manipulate these tools but also the adaptability to switch between them efficiently and use them correctly in different cooking contexts. This paper reviews the latest developments in robotic cooking platforms, examining their design, performance, and public perception. It also covers various technologies critical for building robotic chefs, categorizing these advancements into need and importance, emerging technologies, different techniques, and future challenges. Furthermore, it addresses the technical and practical obstacles that currently hinder their widespread implementation.

Keywords: Chef Robot, Robotic Cooking, HRI

1 Introduction

The enormous surge in the adaptation of robots in numerous sectors has transformed old processes, bringing efficiency and precision to tasks previously considered too complicated for automation. Among these improvements, the concept of cooking robots has evolved to transform both home and commercial kitchens. A cooking robot differs from a smart device or traditional automation by its ability to cook various dishes, make sensory-based decisions, learn different recipes, adapt to user preferences, and integrate into human kitchens [1], [27].

Technological advances like standard dexterous robotic arms, deep learning, powerful computer vision models, and advances in modal sensors have brought us closer to fully autonomous cooking robotsThese include sensors, tactile grippers, ingredient and recipe recognition, and understanding of human input. Devices can perform tasks like cutting, stir frying, washing, and other tasks. Robot chefs also help to alleviate labor shortages, save cooking time, and improve food availability and quality [19].

Most households continue to rely on traditional tools and methods, with only incremental ergonomic and production cost improvements over the centuries. Cooking takes up substantial time, and for many, the only alternatives to home-cooked meals are mass-produced, often nutritionally inferior factory meals or costly restaurant options. Chef robots offer numerous advantages. They underscore the pressing need for a more decentralized approach to culinary productivity, which robotic chefs could partially or largely provide. In commercial settings, employing chef robots can save cost and space, as robots do not need to take breaks and can come in different sizes. In addition, robots can work longer hours, allowing restaurants to conduct business during holidays or for more time, enabling more flexibility for both the restaurant and its patrons.

As Figure 2 illustrates, current cooking robot research is divided into multiple areas. These can be divided into human experience, robotic development, and machine learning. Human experience topics include social acceptance, ethical considerations, affordability, safety, and hygiene. Robotic development covers sensory feedback, modeling objects, evaluating performance, and object manipulation. Machine learning topics span areas such as computer vision, food recognition and classification, understanding human input, and estimating human actions and poses.

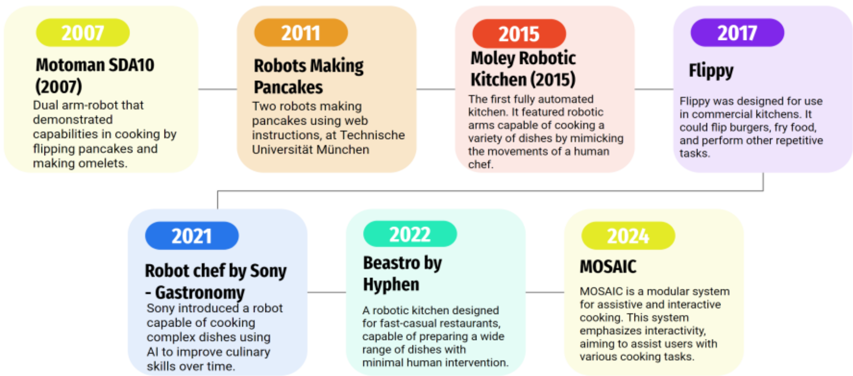

Fig. 1. A brief history of cooking robot research. This figure gives background information about the history of cooking robots and talks about the importance of each robot.

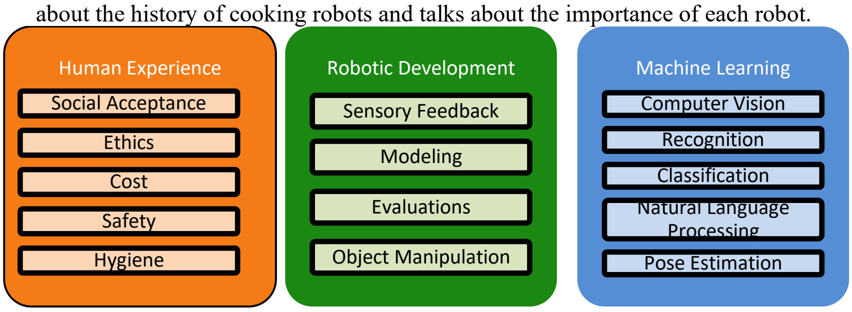

Fig. 2. Different areas of cooking robot research, with a specific focus on Human Experience, Robotic Development, and Machine Learning.

This paper reviews the latest developments in robotic cooking platforms, examining their design, performance, and public perception. It also covers various technologies critical for building robotic chefs, categorizing these advancements into need and importance, emerging technologies, different techniques, and future challenges. Furthermore, it highlights the potential of robotic chefs to revolutionize and automatize cooking while addressing the technical and practical obstacles that currently hinder their widespread implementation.

The Need and Deployment: Apart from the numerous benefits of using cooking robots in households, restaurants, and the food industry over traditional automation machines and manual labor, there are some specific needs. However, there are associated technical challenges as well. For example, the elderly and people with disabilities (PWD) have special needs for such robots, as kitchens are often poorly designed for people with limited mobility, cognitive function, or other disabilities. Robots can also offer more clean, safe, and efficient cooking while working longer hours and in various types of kitchens. However, current technology faces many setbacks that make it difficult for robots to prepare ingredients and cook various recipes, especially in noisy real-life environments. Judging the quality of food is a highly subjective matter, but improving robots requires objective and quantitative feedback. As for the cooking process itself, many robots have preset recipes and hardcoded control sequences, limiting uses to a certain environment or food. Food objects and actions are also difficult to clearly model and compute, requiring engineers and robots to make many intermediate and specialized steps to accomplish tasks simple for humans. Robots that are versatile and robust are not affordable for everyday use, causing difficulty in creating a robot that is affordable and performs well.

Studies have provided evidence that the elderly and PWD can benefit significantly from cooking robots. [8] explains how the kitchen poses a large risk for older people from misuse of kitchen appliances, cooking tools, and cutlery. The study investigated physical difficulties and safety in cooking tasks for older people, with many of the subjects having to adopt awkward postures due to problematic kitchen designs. Subjects stated problems with bending, stooping, lifting, opening packages, cleaning cooking appliances, mobility, cutting, stirring, and being tired, as well as burning and packaging accidents. Kitchen designs may also be inaccessible and difficult to work with for PWD, such as reaching a cabinet for someone in a wheelchair. Cooking robots can reach places that may be impractical for some individuals to access with the combination of joints, cameras, and sensors. The study conducted in [23] found the kitchen was the second most common place for domestic accidents to occur, with fires and burns caused by memory problems in elderly people.

Hygiene and Safety: Robotic technology can offer a wide variety of advantages over manual cooking for the average person. Robots have been used for quality inspection of meat [14], so they can ensure that the ingredients meet the standard of the user. Robots do not have a risk of illness and infection from raw and contaminated foods, ensuring that the workers do not get sick. In addition, robots do not have a risk of injury as severe as humans. Mechanisms can be put in place to protect the robot from burning due to stovetops and ovens, cutting, or crushing itself. Robots can also detect hazards that humans may not notice or alert others fast enough about, such as fires [27].

Efficiency: Using robots can offer more consistent and precise results when dealing with food [14]. Humans can forget, misplace, and mismeasure food items while robots are programmed to have exact timings and positions to prepare food. In addition, the robot can search the internet and identify properties of foods, learn new cooking recipes and techniques, and parse manuals to learn how to use a cooking device [9]. This provides an advantage over humans, as online information may not always be accessible or available to humans. For example, if a human is cooking on a stovetop or working in a restaurant with a high volume of orders, it would be inconvenient for the human to stop cooking and search up information.

Flexibility: Learning new recipes requires time and is prone to error, while robots can create new dishes through interpreting an online recipe such as in [2] or observing a video such as in [19]. Existing datasets such as [3] and [12] provide vision and sensor-based data, which could include a wide variety of recipes in the future. Restaurants have a set menu and limited options that can be expanded through robots. Robots can adapt to user preferences and provide a customized dining experience, which can greatly change restaurant experiences.

2 Technical Challenges

Formulating Subjectivity: One of the main difficulties in measuring the efficiency and success of cooking robots has been finding an objective way to evaluate subjective qualities. One quality that is highly subjective is taste, as not only do individuals inherently have different preferences for tastes, but their previous experiences and expectations for food influence their opinions. A benchmark for measuring taste has been proposed in [19], but has yet to be widely adopted. [5] uses a numerical evaluation of taste, texture, and appearance on a scale of 1-10 to compare a human-made pancake versus a robot-made pancake. The human pancake was always set to a score of 5-5-5, which can change the scores of the robot depending on the human making the pancake. In addition, creating statistically significant data is difficult as testing a large number of samples or eating samples over multiple days is difficult due to finite appetite, fading memory, and a high cost of time and ingredients [11].

Cooking Setup: Another limitation of cooking robots is the setup and environment in which the robot performs. Currently, robots work in controlled and favorable environments, but it has yet to be seen whether robots can successfully cook in complex environments. Ingredients, heating up the pan, and cleaning up workstations must be manually set up for the robot. [5] hardcoded picking up and returning tools, which required tools to be placed in exact positions. The hotplate was also preheated and oiled beforehand. The robot learned by observing a human making a pancake recipe and analyzing the trajectory of the right wrist, restricting the human to making the recipe only with their right hand. In [11], an omelet-making robot needed the tools to be in a set location as well as eggs to be put in a cracker manually. Other factors such as heat level, duration of heating, and pouring bowl contents were constant, which limits evaluating a robot's performance to a specific, predefined recipe. In addition to having hardcoded control sequences, robots are currently trained using either video footage [18], motion capture equipment [22], depth cameras [3], or inertial sensors [3], limiting widespread usage.

Actions: An action is any task that a robot can perform. Handling actions and action parameters is difficult as well, as there is a large amount of implicit information that

robots may not have access to. For example, in [24], there was difficulty in modeling objects and coordinating both arms for the specific task of stir-frying. [13] aims to define actions and constraints for a robot to perform a specific goal, such as loading a dishwasher or setting trays in the oven, which non-expert users may find challenging. [2] explains how a pancake-making robot must not only pour the right amount of batter at the right position in the pan but also account for physical constraints and optimize movements such as the height to pour a pancake mix to allow for a circular pancake. [20] describes how recipes often have incomplete or ambiguous instructions that would make sense to a human, but not a robot. To cut carrots, humans know that you must place the carrots on the cutting board and hold the knife, which robots do not know. Robots must infer intermediate motions and perform them in the correct order.
Affordability and Quality: There seem to be tradeoffs between cost, speed, and precision. Moley Robotics offers a robot with dual arms that can cook from scratch, prepare ingredients, use pots and utensils, clean up after itself, choose from over 5000 recipes, and learn the user's recipes with the movements and speed of an expert chef [1]. However, the high-speed and high-precision robot costs $340,000, making it unaffordable for the average family. On the other hand, [15] developed a cooking robot for the elderly and PWD with the goal of being affordable. However, the cost of maintaining hygienic food for the robot would be too expensive for the average user, so the robot is unable to prepare ingredients. Similarly, [16] designed a low-cost robot with medium precision and low speed, which is suitable for domestic use. Employing robots in restaurants can also provide more speed and precision than human chefs, as robots do not tire, but come with the costs of staff training and maintenance.

3 Various Techniques and Skills

Human tasks related to cooking are vast but typically include things like slicing, cutting, peeling, spreading, mixing, pouring, and wiping. Some cooking tasks require different skills than others, meaning robotic techniques are required for both cooking tasks and human-like skills such as planning, environment adaptability, and perception. While there are a vast number of techniques used for cooking robots, common features to mimic such tasks include robot manipulation, machine learning, and multimodal sensors. Concerns revolving around how the robot might detect, identify, and manipulate an object can be solved with these techniques, creating a robust and efficient system. Tasks that require manipulation and detection are generally dependent on sense and perception, which can be achieved through multimodal sensors and machine learning techniques such as computer vision and deep neural networks. Subsequently, relevant algorithms are needed for such tasks. This section will survey tradeoffs, concerns, and implementation of such techniques.

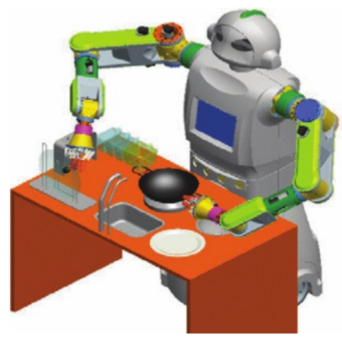

Fig. 4 A dual arm humanoid robot [24].

Robot Manipulation: General robotic manipulation for robotic cooking includes a dual arm manipulation system [4]. The dual arm manipulation system in most robotic cooking consists of bimanual manipulation, which is defined as the physical interaction using two hands on the same object [4]. An example of this system can be seen in Figure 4, where a dual-arm cooking robot is doing a cooking-specific task using bimanual manipulation [24]. Robotic manipulation is also necessary for mimicking cooking activities that require more mechanical skills. This can include opening, peeling, closing, and pouring items [10], [6].
Machine Learning Approaches: Machine learning (ML) is revolutionizing robotic cooking by enabling machines to learn and adapt to culinary tasks. Many ML approaches, including computer vision, natural language processing, and deep learning, synergize to create sophisticated robotic cooking systems capable of handling diverse recipes and interactions with human users.
Computer Visions: A machine learning approach in robotic cooking can help create artificial perceptual skills. One way to do this is through the use of computer vision. Computer vision can be used to determine the position, type, and quality of the food item [7], such as whether an object is rotten, fresh, or raw. One approach is to use cameras and computer vision to record and track the positions of kitchen tools to match a demonstrator's movements [5]. Learning by demonstration can be done by using computer vision alongside computer vision libraries. One popular library is OpenPose [5], which provides users with a variety of human poses along with tracking different parts of the human body.
Natural Language Processing: Natural Language Processing (NLP) in robot cooking systems can help minimize error when it comes to following a recipe and also allows for more of a collaborative effort between humans and robotic systems in regard to cooking and deciding on recipes [21]. Translating recipes into simpler steps using NLP can be useful in solving concerns revolving around the ambiguity of the kind of object one may need for a recipe. Giving clear instructions through natural language with robotic cooking systems can solve these types of ambiguities. NLP can also be used to help with mimicking the way humans plan their cooking tasks when following a recipe [18]. One approach is to use NLP along with web instructions to allow for motion planning for cooking robotic systems as seen in [2],[20].

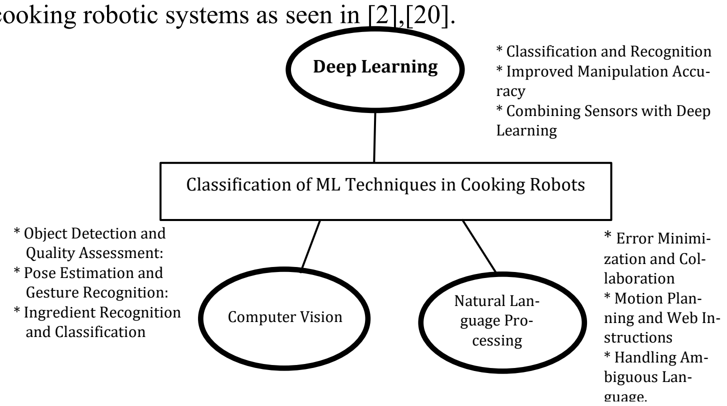

Fig. 3. A classification of the different machine learning techniques.

Deep Learning for Cooking Tasks: As stated previously, some cooking tasks may require skills such as precise coordination and subtle motion. One way to mimic such skills is to use Deep Learning techniques, which allow the classification of different textures, tastes, and shapes in cooking [17]. Concerns around the automatization of classification in cooking robotic systems can also be solved through the use of Deep Learning neural networks and CNNs (Convolutional Neural Networks) [17]. Deep Learning neural networks can also be used to improve robot manipulation accuracy and interpretation [13]. Balancing accuracy and speed of identification can be done through libraries such as OpenCV-Python as seen in [17]. One approach to improve robot manipulation accuracy and interpretation is by using Deep Learning Graph Neural Networks (GNN), which allows for generalized yet accurate instructions for robots [13].
Data Collection: Data collection is extremely important in robotic cooking because it allows for these systems to get better at recognizing mistakes and become automatable. Some may have apprehensions about the way data is collected and may be curious as to how data is collected on cooking robots. Conclusions
Robotic cooking can save time, encourage healthy eating habits, and lower operational costs in commercial settings. As technology advances, these robots are likely to become more adaptive, efficient, and accessible, making them an essential component of future kitchens.

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