SnapChef: AI-powered Recipe Suggestions[⋆]

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Abstract

AI-powered technologies are becoming pervasive, and offer endless possibilities for novel consumer applications. This paper describes the comprehensive process of designing, implementing, and evaluating SnapChef, an innovative recipe recommendation application. The results of the System Usability Scale (SUS) study conducted over a software prototype using the Android platform yielded overwhelmingly positive user feedback, indicating a high level of satisfaction with the application's usability. Despite noted imperfections in image recognition accuracy, we anticipate significant enhancements in this aspect as AI technology continues to evolve and mature over time. These findings underscore the potential for continual improvement and optimization of our application to meet user needs and expectations in the dynamic landscape of AI-driven technologies.

Keywords

Computer vision, Image recognition, Large Language Models, Artificial Intelligence

1. Introduction

Food waste is a major global issue [1]. In the United States, 38% of food produced annually is not consumed, representing a costly issue equivalent to approximately 1.8% of the GDP. [2]. Despite often being overlooked, approximately two-thirds of the food discarded in households is due to spoilage before it can be utilized [3]. Food waste may occur in different stages in the supply chain, from production and harvesting, to retail and distribution, to consumer behaviour. It may be a result of overproduction, inefficient storage, transport issues, as well as strict aesthetic standards. Consumer behaviors such as overbuying and improper storage also contribute significantly, as well as date label confusion. Regardless of the reasons for underutilizing our food, it is imperative to address this issue because agriculture is an activity that demands extensive resources, in terms of land, water and labor [4].

Over the last decade we have witnessed a boom of artificial intelligence (AI) technologies. *Computer vision* has advanced significantly leveraged by deep learning approaches, in particular convolutional neural networks [5, 6]. One the other hand, generative AI also promises a plethora of new applications [7]. For example, generative AI has found novel applications in creating realistic virtual characters for video games, generating personalized content for marketing campaigns, and designing complex molecules for pharmaceutical research [7]. While still in their infancy, Large Language Models such as GPT-4 for natural language processing, BERT for understanding context in text, and T5 for text-to-text transformations offer possibilities to apply artificial intelligence to help solve novel problems to bring about positive changes to our society [8]. Despite their potential, these technologies face several challenges due to their recent development; one key consideration is their lack of complete accuracy, which makes them susceptible to errors and incoherent results. However, significant advances in the technology's responsiveness are expected over time.

In this work, we leverage recent trends in AI technologies to address the issue of food wastage that occurs as a result of consumer behavior. We introduce *SnapChef*, a mobile application that allows users to photograph food ingredients in their kitchen cupboard or fridge and receive a list of recipe recommendations. This process involves two steps: first, computer vision techniques identify the set of food ingredients; second, a Large Language Model generates a list of recipe suggestions based on

ICAIW 2024: Workshops at the 7th International Conference on Applied Informatics 2024, October 24–26, 2024, Viña del Mar, Chile

[⋆]We wish to credit ChatGPT for suggesting the name "SnapChef" for our application.

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Table 1
Research related to this study, in the areas of food recognition, recipe recommendation and smart fridges.

Citation	Year	Article Name	Image recognition	Recipe recommendation	Smart fridge
[9]	2009	A food image recognition system with multiple kernel learning.	X		
[10]	2013	EatChaFood: challenging technology design to slice food waste production.	X		X
[11]	2016	Smart refrigerator: A next generation refrigerator connected to the IoT.	X	X	X
[12]	2017	Low-cost smart refrigerator.	X		X
[13]	2017	Smart fridge design using NodeMCU and home server based on Raspberry Pi 3.			X
[14]	2017	The design of a smart refrigerator prototype.			X
[15]	2017	Exploiting food choice biases for healthier recipe recommendation.		X	
[16]	2018	Using two government food waste recognition programs to understand current reducing food loss and waste activities in the US.			
[17]	2018	The implementation of IoT based smart refrigerator system.			X
[18]	2019	Monitoring Potato Waste in Food Manufacturing Using Image Processing and Internet of Things Approach.	X		
[19]	2022	Food Recognition and Food Waste Estimation Using Convolutional Neural Network.	X		
[20]	2021	Computer vision based two-stage waste recognition-retrieval algorithm for waste classification.	X		
[21]	2021	Intelligent refrigerator.			X
[22]	2021	CookingQA: answering questions and recommending recipes based on ingredients.		X	
[23]	2023	Using artificial intelligence to tackle food waste and enhance the circular economy: Maximising resource efficiency and Minimising environmental impact: A review.			
[24]	2023	Novel Nutritional Recipe Recommendation.		X	
[25]	2023	Health-guided recipe recommendation over knowledge graphs.		X	
[26]	2023	Towards Health-Aware Fairness in Food Recipe Recommendation.		X	
[27]	2024	Large language models can help boost food production, but be mindful of their risks.			
[28]	2024	Chef Dalle: Transforming Cooking with Multimodal AI.		X	

the identified ingredients. The main contribution of this work is the integrates both image recognition and LLM technologies. Unlike most previous works, as discussed in Section 2, we combine food image recognition with recipe recommendations.

The structure of this paper is as follows. Section 2 presents related work. The design of the mobile application is outlined in Section 3. Subsequently, we describe the implementation (Section 4). We evaluate the application by means of a usability study describe in Section 5. Discussions are presented in Section 6, and Section 7 concludes.

2. Related Work

Table 1 presents a summary of related work. We can see that there have been different approaches to address the specific problem of food waste, and other related problems as well. For example, hardware such as Arduino Uno has been used for the identification of radio frequency tags (RFID) [14], or in others cases similar approaches but using servers based on Raspberry Pi [13, 11]. Although these approaches use different hardware, they share the same objective of reading RFID tags, which seems to be a fairly important trend in the last decade. This solution may be viable, but it has the limitation that items without RFID tags, such as fruits and unpackaged vegetables cannot be handled by this method [11]. This represents a significant limitation, as these are the types of foods that are typically stored in refrigerators and thus easily perishable.

Generative AI technology has only been accessible in recent years, which explains why it was not a trend for it to address this issue in the past. However, the use of image recognition for food has proven to be very effective. This is exemplified by the application of a convolutional neural network, that was used to determine how much had been eaten from a plate with an accuracy greater than 98% [19]. Similarly, a system devised to monitor potato waste exhibited the capability to assess potato states at a rate of one potato every 1.5 seconds, achieving an 81.25% accuracy on a large scale [18].

In relation to the issue of food waste and its integration with smart refrigerators, this work can be differentiated from other similar approaches by implementing novel two different types of AI tools.

3. Design

To tackle the issue of consumer-driven food wastage, aimed at facilitating user interaction, we introduce a mobile application serving as a visual interface. The primary functions of this software entail food detection and recipe generation. To ensure a modular design, these tasks are executed through the utilization of APIs. This section delineates the proposed architectural framework.

Figure 1 presents the architecture of the application, which is composed of the following components:

- User: Represents the entity that interacts with the application.
- Interface: Contains the application logic.
- Image Recognition API: Specifically designed to identify food items in images.
- Large Language Model (LLM) API: Provides advanced natural language processing capabilities.

The flow of control proceeds as follows: Initially, the user chooses an image through the application interface, either by capturing a photograph using the mobile device or selecting a file from the filesystem. Subsequently, the image is forwarded to the initial API for image recognition, which furnishes a string containing the identified ingredients. Upon receipt of this information, a request is dispatched to the LLM API. This module yields a compilation of recommended recipes, which is then presented to the user.

Figure 2 presents the wireframes for the proposed application. Figure 2a shows the home screen where a canvas and three buttons are displayed. The *camera* button which enables a photograph to be taken using the mobile device. The *gallery* button enables an image to be selected from the gallery. The canvas is initially blank; however, upon selection of an image from either the camera or the file system, it is displayed within the canvas. The *continue* button permits user navigation to the subsequent application screen.

Figure 2b shows the second screen of the application, which consists of a modal window that indicates the previously found ingredients. Finally, Figure 2c shows the generated recipes. These are displayed in the form of cards, and on each card we can find a different recipe. By clicking on a card, the instructions to follow for that particular recipe are displayed.

4. Implementation

In this section, we firstly justify the rationale behind the selection of the technologies used (see Section 4.1). We then describe the implementation of the food image recognition phase in Section 4.2 and the recipe generation phase in Section 4.3. Finally, we show an example run of the application in Section 4.4.

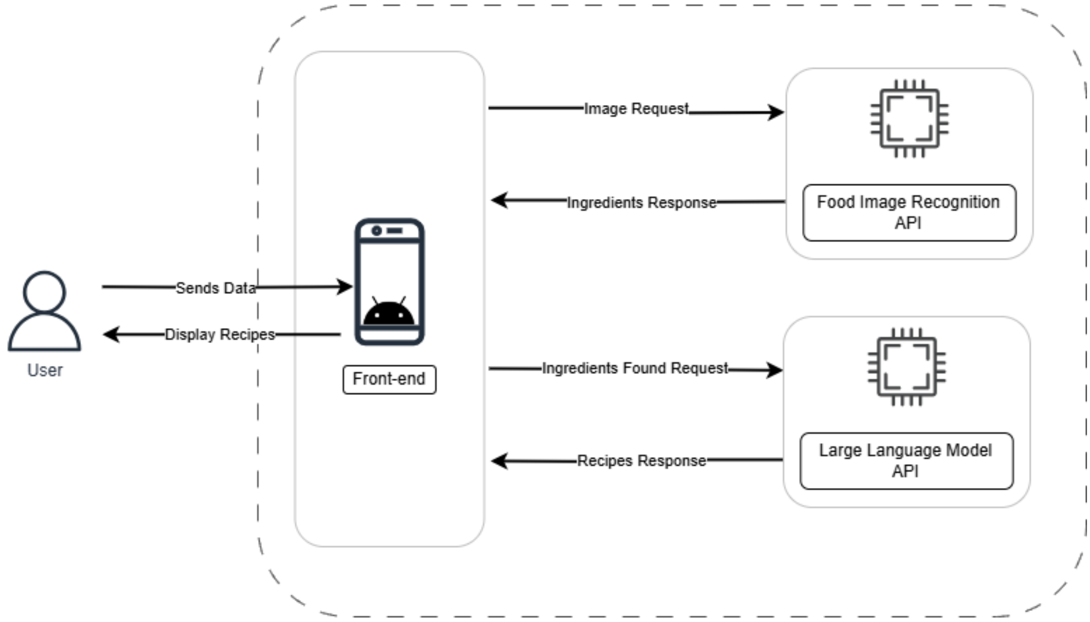
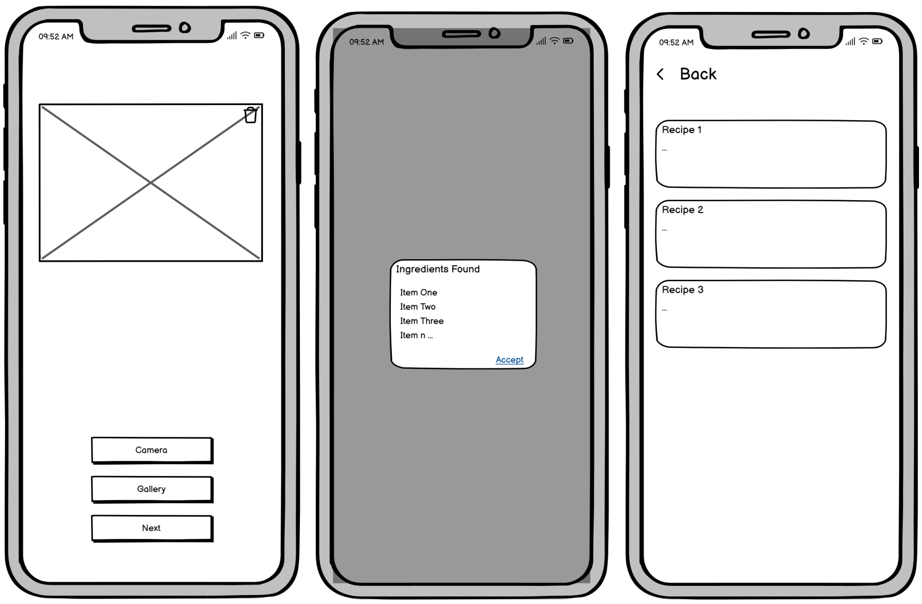


Figure 1: Architecture of the application.



(a) Landing screen. (b) Modal of ingredients. (c) List of recipes.

Figure 2: Wireframes of the final design of the application.

4.1. Technology Selection

Framework The Flutter[1] open source framework developed by Google was selected for the development of the application. While for the purposes of our prototype we produce code for the Android platform, we selected Flutter as it offers numerous advantages for mobile application development, including the ability to create cross-platform apps with a single codebase for both Android and iOS, which streamlines development and maintenance. Its hot reload feature speeds up the development process, while its compilation to native ARM code ensures high performance. Flutter provides a rich set of customizable widgets for consistent UI design across platforms and is supported by a strong community and Google,

[1]https://flutter.dev/

offering extensive resources and plugins. Additionally, it allows access to native features and ensures consistent behavior across platforms, making it a robust and efficient framework for modern mobile app development.

Food Image Recognition Technology In the early stages of project implementation, image recognition models specifically for food recognition were studied. Logmeal[2], a company that specializes in "artificial intelligence for food recognition and nutritional analysis", has pre-trained image recognition models for many different types of food. The Logmeal API[3] was tested and found to correctly identify different types of food. This API sends images in JPEG format, with a size not exceeding 10.48MB. It then returns a JSON type object containing the results of the found elements. This is then used to return food found within the body of the object.

Recipe Generation Technology We also examined Large Language Models capable of assembling recipes based on previously identified ingredients provided by prompts. ChatGPT was one of the candidates considered for this task and was deemed to be the best choice due to its ease of integration and simplicity in returning responses since it can be modeled as a JSON object instead of a simple text string. Choosing ChatGPT over other existing large language models offers the advantage of advanced conversational capabilities and contextual understanding, thanks to its extensive training on diverse datasets. Additionally, it benefits from continuous updates and improvements by OpenAI, ensuring state-of-the-art performance and reliability in generating human-like text.

4.2. Step 1: Food image recognition

As shown previously in Figure 2a, the initial home screen provides the user with three buttons for using the camera or selecting an image from the file system. After pressing the *Continue* button, the image is selected and verified that it is no larger than the originally specified dimensions. If the image is too large, a function is executed to reduce the size of the image. Then an HTTP REST request of type `POST` is made to the Logmeal API. The parameters required and used by this request are as follows:

```
URL: https://api.logmeal.es/v2/image/segmentation/complete/v1.0
Parameters:
language = spa
Authorization Bearer Token
Token = <Token of the LogMeal application>
Body: FormData
Image= <file of the image to be sent by the application>
```

This Logmeal API returns a body in JSON format with the identified ingredients within its elements. If the prediction is deemed to be appropiate by the user, the application will navigate to the second screen where the ingredients are shown within a modal dialogue box. If the request generated an error, an appropriate message is displayed. The sequence of events is shown in the sequence diagram in Figure 3.

4.3. Step 2: Recipe Generation

Once in the second screen, the second API that calls ChatGPT will be automatically triggered. Recall the a JSON object is obtained from ChatGPT. This is accomplished by sending two prompts. The first prompt provides contextual information at the system level. In particular, the requirement is to respond in JSON format only, making it easier to extract the response once it is received. The second prompt is a request to return a list of recipes to be displayed to the user based on previously found ingredients, and write descriptions for the fields that must contain that information when printed. Figure 4 presents the prompts used by the application.

[2]https://logmeal.com/
[3]https://api.logmeal.es/docs/

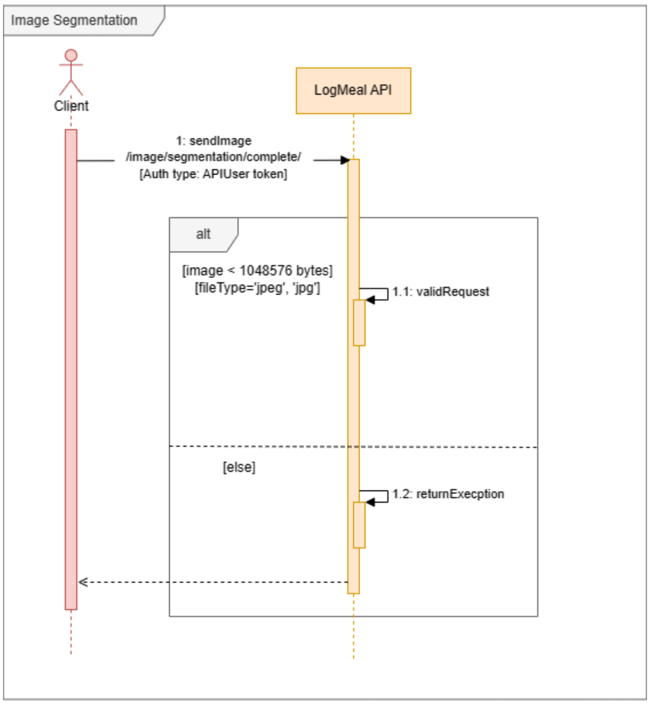


Figure 3: Sequence Diagram of the Logmeal API.

As with the Logmeal API, a Bearer token is sent to authorize the sending of the requests. Additionally, a JSON document with the following fields will be sent in the body of the request:

```
URL: https://api.openai.com/v1/chat/completions
model= gpt-3.5-turbo
messages= <List of key-value pairs as follows>
role= <system, user>
content= <prompts indicated previously, one for the system that tells ChatGPT
how to return the information, and the role of the user that is the prompt where
the ingredients found above are indicated, and the structure of the response
is specified and what value each field should have.>
```

Figure 5 shows the sequence diagram of the ChatGPT API calls.

Subsequently, ChatGPT generates an response that will be stored inside the application. The body of the answer will be extracted where the information of the recipes generated by ChatGPT will be found. This information is extracted inside cards that will be shown to the user indicating the name of the dish, the time of the recipe and how many people the recipe is for. Inside each card there are step-by-step instructions to prepare the recipe.

4.4. Example Run

Figure 6a displays the home screen, where the user has already selected an image with foods to use. Figure 6b shows the modal box presenting the list of ingredients once the Logmeal API has responded. Finally, after closing this modal box, Figure 6c shows the recipes recommended by the ChatGPT API in the form of cards. Each card contains information about the name of the recipe, preparation time and number of servings. In addition, step-by-step instructions are provided on how to make the recipe.

Figure 4: ChatGPT Playground prompt used in the application.

5. Evaluation

Usability testing plays a pivotal role in the development and refinement of products and systems, ensuring they meet the needs and expectations of users. By systematically evaluating the user experience, usability testing helps identify and address usability issues early in the design process, ultimately enhancing the product's effectiveness, efficiency, and user satisfaction. Through direct observation and feedback from representative users, usability testing provides valuable insights into how users interact with the interface, highlighting areas for improvement and informing iterative design iterations. Moreover, by uncovering usability barriers and usability bottlenecks, usability testing mitigates the risk of costly redesigns and product failures post-launch, contributing to overall product success and market competitiveness.

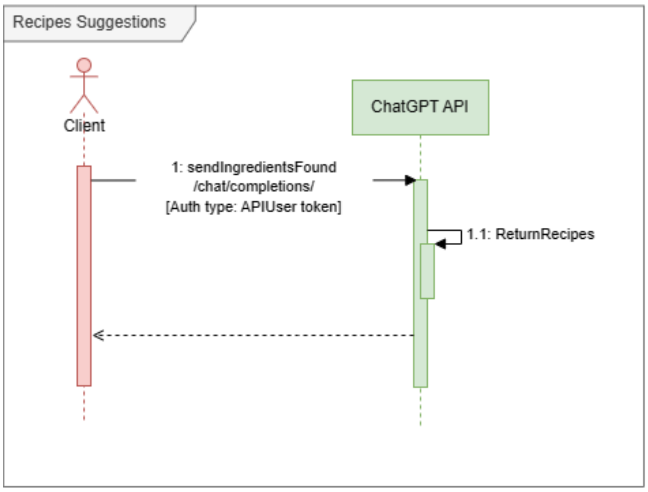
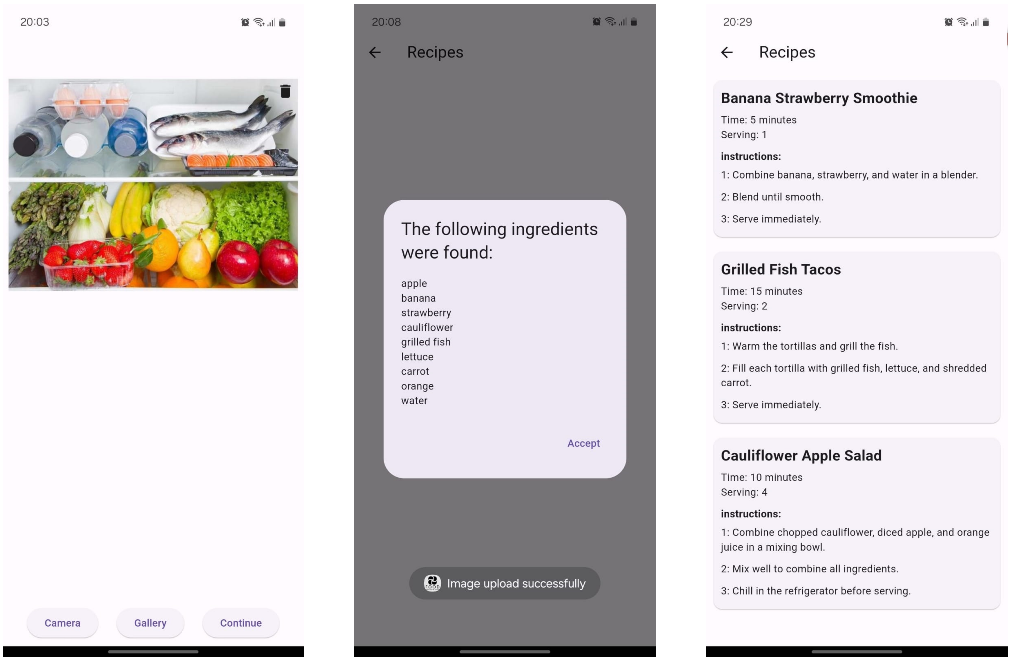


Figure 5: Sequence Diagram of the ChatGPT API.



(a) Home screen of the app.

(b) Modal showing the ingredients found.

(c) Recipes suggested according to those ingredients.

Figure 6: Screenshots showing an example run.

Experiment Setup On May 6, 2024, a usability assessment was conducted involving 25 participants enrolled in the Data Structures undergraduate course at Jorge Tadeo Lozano University (see Figure 7). The evaluation entailed individualized interactions with an image sourced on the Internet by each participant featuring various ingredients. This was done so that each participant would select a different image. Participants utilized the application's photo-capture feature to process the image and subsequently reviewed the returned recipe recommendations. Following this task, participants completed a usability survey adapted from the System Usability Scale (SUS) questionnaire[4], containing Likert scale responses ranging from 1 (strongly disagree) to 5 (strongly agree). Responses were collected using Microsoft Forms. Table 2 presents the questions given to each participant, and the mean score awarded to each question.

[4]https://usabilitygeek.com/how-to-use-the-system-usability-scale-sus-to-evaluate-the-usability-of-your-website/

Figure 7: Usability evaluation activity with students at Jorge Tadeo Lozano University.

Table 2
System Usability Scale (SUS) questionnaire and mean scores obtained.

Statement	Mean Score
I think that I would like to use this system frequently.	4.30
I found the system unnecessarily complex.	2.00
I thought the system was easy to use.	4.38
I think that I would need the support of a technical person to be able to use this system.	1.23
I found the various functions in this system were well integrated.	4.42
I thought there was too much inconsistency in this system.	2.09
I would imagine that most people would learn to use this system very quickly.	4.90
I found the system very cumbersome to use.	1.47
I felt very confident using the system.	4.76
I needed to learn a lot of things before I could get going with this system.	1.19

Response Validation Following the collection of participant responses, a data cleaning or quality control procedure was implemented to ensure response consistency and identify potentially random responses. The System Usability Scale (SUS) questionnaire facilitated this process, as each of its 10 questions is presented both positively and negatively, resulting in 5 generated questions. During the validation process, responses to positively and negatively framed questions were compared, with a permissible difference value set at one. Responses showing a discrepancy of more than one were deemed invalid. For instance, it would be incongruous for a participant to evaluate the statement "I found the system unnecessarily complex" similarly to "I thought the system was easy to use." Consequently, out of the initial 26 responses provided by participants, 5 were deemed inconsistent and omitted from analysis, leaving 21 valid responses for evaluation.

Results obtained Figure 8 presents the results obtained for questions 1–6. Figure 8a presents the results to the statement "I think that I would like to use this system frequently". The majority of responses to this question are 4 (agree) or 5 (strongly agree). Only two participants respond with a 3 (neither agree nor disagree). The mean score is 4.30, indicating that overall most participants strongly agree with the statement.

Figure 8b shows the results for the statement "I found the system unnecessarily complex", where the majority of the responses disagree. We observe a similar trend in Figure 8c, with the statement "I thought the system was easy to use". In both cases, we can identify that few people consider the application to be difficult or complex only four people have this opinion.

Figure 8d shows that, according to the participants, the various functions of this system were well integrated. In contrast, Figure 8e reveals that most of the responses to the statement "I thought there was too much inconsistency in this system." are positive, although at this point there is a slight increase in disagreement compared to the other statements. The reason for this is due to some particular cases where the application had small failures in identifying ingredients. However, the average results for this statement show a mean score of 2.09. Although not negative, improvements can always be made to increase this score, as mentioned in the 6 section.

Figure 9 presents the results obtained for questions 7–10. Figure 9a we find the most positive statement of those asked above: "I think that I would like to use this system frequently". Only two votes separate this one from achieving a score of 5, with an mean score of 4.90. It is encouraging to know that the participants believe that other people would learn to use the system quickly, which relates to the statement in Figure 9c where most users felt confident in using the application. Finally, we can deduce from the statements in Figures 9b and 9d respectively, most users do not think that the system is difficult to use nor that much expertise is needed to manipulate it. The last statement is the highest rated statement of disagreement with an average rating of 1.19.

6. Discussion

The total usability score computed for the system was 87.14 points (out of a total 100 points), which indicates that the system is excellent in terms of usability. However, there are some areas for improvement, and in addition to ten usability questions, a free-text suggestion or comment box was provided. In this space some positive comments and suggestions for improvement were received, such as that the interface should be improved. It was also commented that image recognition does not always work correctly. Some of the comments received included:

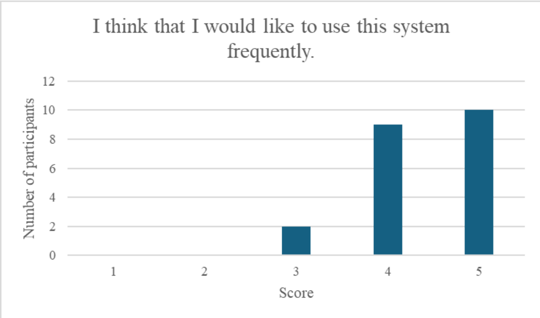
- *The application is very clear and recognizes the various ingredients. It presents a clearer vision when cooking and learning new gastronomy recipes.*
- *It needs to slightly improve the ingredient recognition functionality*
- *It has flaws like any other AI, like hallucinations*
- *It is necessary to improve the identification system*
- *I think the accuracy of scanning or processing the images should be improved.*

We note that, according to the user comments, the flaws in the application primarily stem from external dependencies, such as the accuracy of data sources and the reliability of third-party APIs. As AI technologies mature and become more sophisticated, performance issues related to these dependencies are expected to diminish, resulting in a more robust and reliable application.

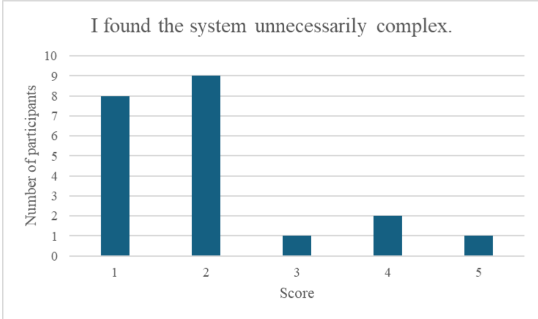
As such, the application demonstrated, overall, a favorable reception among users. However, several areas for improvement have been identified, particularly the visual interface, which could be enhanced to be more intuitive and visually appealing. Additionally, incorporating new functionalities could significantly improve the user experience. Another crucial aspect for improvement is the accuracy of food predictions. Although the identification of most ingredients was satisfactory, integrating a newer and more advanced API could further enhance the quality of the recipes provided. The ChatGPT API effectively fulfilled its role in delivering recipes based on specific ingredients. While the accuracy of some ingredient predictions was occasionally suboptimal, none of the experiments revealed errors that adversely affected the user experience, indicating that this component may not require immediate adjustments.

7. Conclusions

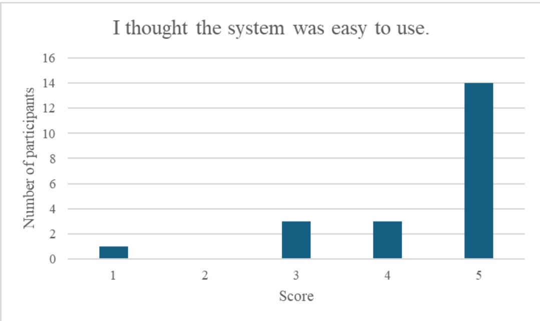
Recent advances are driving the proliferation of AI-powered applications across various industries. This rapid development is set to make AI an integral part of everyday technology, enhancing efficiency



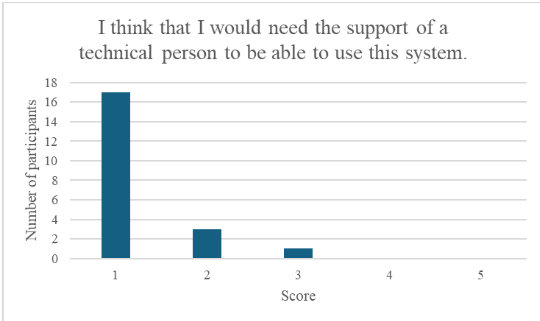
(a) “I think that I would like to use this system frequently”



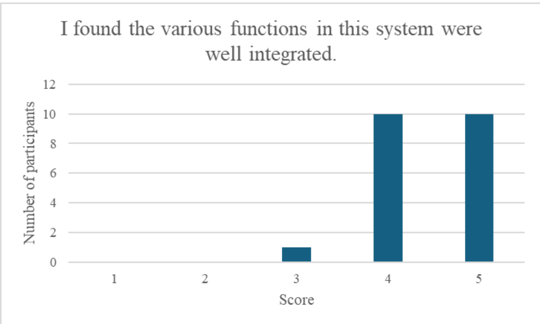
(b) “I found the system unnecessarily complex”



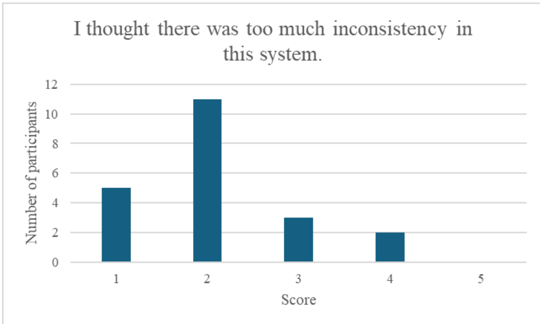
(c) “I thought the system was easy to use.”



(d) “I think that I would need the support of a technical person to be able to use this system”



(e) “I found the various functions in this system were well integrated”

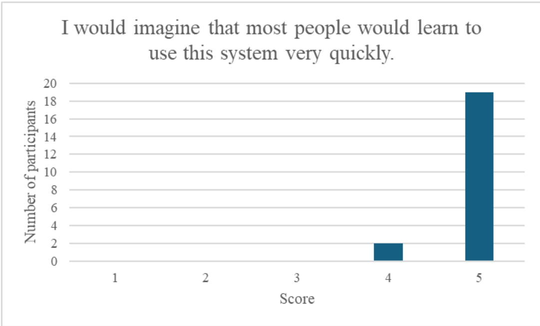


(f) “I thought there was too much inconsistency in this system.”

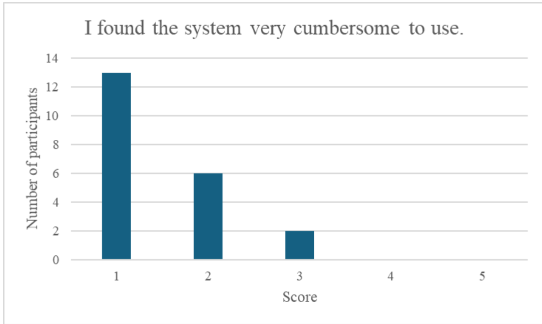
Figure 8: Responses to questions 1-6 of the usability questionnaire

and innovation in numerous fields. AI has the potential to significantly reduce food wastage in the food industry by optimizing supply chain management, improving inventory tracking, and predicting demand more accurately. Additionally, AI-driven applications can help consumers by suggesting recipes based on available ingredients, thereby minimizing household food waste. SnapChef underwent usability testing with a diverse group of users and received positive feedback for its intuitive interface and accurate recipe suggestions. The application’s ability to enhance meal planning and reduce food waste was particularly well-received, highlighting its practical benefits for everyday use.

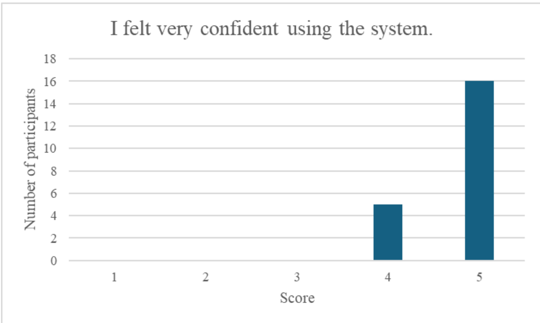
As future work, SnapChef could be significantly enhanced by integrating IoT sensor technology to enable real-time inventory tracking and suggest recipes based on available ingredients. Additionally, taking dietary preferences or restrictions into consideration would personalize the user experience, ensuring that recommended recipes align with individual needs. Moreover, implementing a feature to generate a shopping list of missing ingredients would streamline the cooking process and minimize waste. Lastly, using multi-modal generative AI to generate on-the-fly video tutorials with the recipe instructions would enhance user engagement and facilitate easier comprehension of cooking techniques.



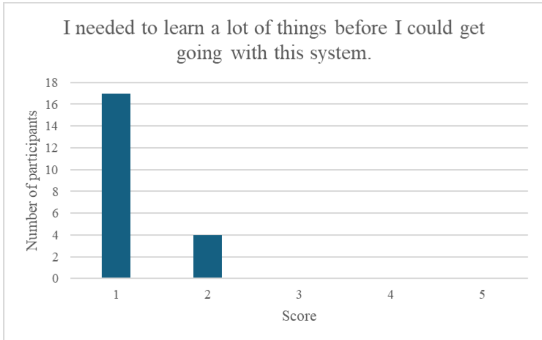
(a) “I would imagine that most people would learn to use this system very quickly”



(b) “I found the system very cumbersome to use”



(c) “I felt very confident using the system”



(d) “I needed to learn a lot of things before I could get going with this system”

Figure 9: Responses to questions 7-10 of the usability questionnaire

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