# AN AI-POWERED MOBILE APPLICATION FOR REDUCING FOOD WASTE THROUGH COST ESTIMATION AND USER AWARENESS

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***ABSTRACT***

*This paper addresses the critical issue of food waste, which contributes to economic losses and environmental harm [1]. We propose a mobile application, Foodnomics, leveraging AI technology to estimate food waste costs and raise awareness among users [2]. The app utilizes image recognition to identify leftover food, estimate portion sizes, and calculate associated costs. Our experiments revealed strong accuracy in classifying common food items but highlighted challenges with less familiar items and regional price discrepancies. The proposed solution builds on existing methodologies by focusing on individual consumer behavior and providing actionable insights. By empowering users to track and reduce their food waste, our project offers a scalable and impactful tool for promoting sustainability and reducing food insecurity [3]. The study concludes with recommendations for further improvements, including expanding the training dataset and incorporating real-time pricing models.*

***KEYWORDS***

*Food Waste Reduction, AI-Powered Cost Estimation, Image Recognition Technology, Sustainability, Consumer Behavior*

## 1. INTRODUCTION

Currently, 9.2% of the global population live in extreme poverty [4]. In the United States alone, 37.9 million people live in poverty. An even greater number of Americans go to bed hungry. 54 million people in the United States battle hunger, including one in five children. One might think that there is not enough food being produced to feed the population. However, the opposite is true. The United States is one of the largest agricultural producers in the world. However, every year the United States wastes 133 billion pounds of food, totaling to 40% of its agricultural output and over than the global average. In fact, the average American wastes up to a pound of food per day, with dramatic increases during the holiday season. If food waste could be reduced, more people would be fed, drastically reducing the current food crisis that America is grappling with. But the effects of wasted food don't only pertain to feeding starving Americans [5]. The Environmental Protection Agency estimates that food waste contributes to 170 million metric tons of carbon dioxide equivalent emissions every year, equal to the annual CO2 emissions of 42 coal-fired power plants [6]. On top of this, the US annually loses almost $500 billion from waste, a huge economic loss that is felt the most upon the classes already struggling the most with rising living prices. Food waste accumulated at every stage of production, from processing to distribution to consumption. Most of the food being wasted can be attributed to the final stage of production:

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consumption. American families simply buy more food than they can eat, which leads to enormous amounts of food waste with ramifications that a vast majority of Americans cannot comprehend. As a result, it is vital to combat this gaping problem normalized within American society. For the people affected from starvation, global warming, and economic insecurity, it is imperative we all focus towards tackling the problem of food waste.

Onyeaka et al. (2023) showcased AI’s potential in optimizing food production and redistribution but lacked direct user interaction. Sigala et al. (2024) demonstrated AI's ability to track and reduce waste in the Horeca sector but relied heavily on commercial infrastructure. Nu et al. (2024) focused on enhancing inventory management in commercial kitchens but required manual data input and had limited applicability to individual consumers. Our project improves on these methodologies by offering a user-friendly, data-driven app that combines image recognition and cost tracking to empower individuals in reducing food waste.

Amidst the rapidly changing environment fostering the growth of artificial intelligence, we advance a software readily accessible to users through both iOS and Android that utilizes Google Gemini to estimate the monetary value of food that users waste [7]. This service allows users to input photos of cafeteria trays or plates that contain their leftovers, and using estimates from Google Gemini, will provide both the total costs and subcosts of the components of food they or others are wasting. One can use this software to track food waste in cafeterias or restaurants over time, gathering invaluable data that they can then share with Directors of Culinary Services on how they can better allocate their resources and mitigate waste. Compared to recent efforts by cafeteria’s that seek to lessen food waste by removing trays, using smaller plates, or offering smaller meal sizes, their attempts all have glaring flaws being that some of them have high transition costs while others might leave students feeling hungry after meals. Also, their efforts may not be backed by data, meaning they may be cutting food production down in all the wrong places. Meanwhile, our service provides raw, meaningful data that identifies then addresses the most prevalent problems that a dining hall should pour their efforts into fixing, of which they can also expect to see the greatest results. Our app Foodnomics is also readily accessible to people on both IOS and Android, being a solution that starts with the people eating the food themselves, instead of a higher management team [8]. This will bring more awareness to the problem of food waste, and empower people to start wasting less, as they can see results immediately on the app, with lower costs of food waste meal by meal.

In our experiments, we aimed to test two critical aspects of the app: the accuracy of the AI model in identifying food items and the reliability of its cost estimation [9]. Experiment A evaluated the model’s precision and recall using a small dataset of 100 images. Results showed high accuracy for common food items but lower accuracy for less familiar ones, indicating the need for a more diverse training dataset. Experiment B focused on cost estimation by comparing AI-generated prices with actual market data from two regions. The findings highlighted discrepancies in region-specific items, emphasizing the importance of user-adjustable pricing for accuracy. Both experiments revealed the app’s strengths in delivering actionable insights while also identifying areas for further refinement, such as improving model robustness and incorporating dynamic pricing adjustments.

## 2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

### 2.1. Accuracy

A challenge that I'm facing is currently making my artificial intelligence that detects individual food components on a plate as accurate as possible. I'm currently Teachable Machine as a way to train the AI the recognize food elements, but even with a lot of time and effort I don't think I can possibly add enough images to the data set to make the AI model as comprehensive as I think the program should be, as the AI recognition aspect is the backbone of my project. Instead, I think using Google Gemini or another sort of already trained model might be more efficient and yield better results, as it can draw from an exponentially larger data set than an AI I can train.

### 2.2. Finance

A challenge I'm experiencing is outside the realm of programming and more in the sphere of finance. Different places across America and around the world have different costs for food. Thus sometimes, the AI model may overestimate or underestimate the cost of wasted food. As a result, I could implement a feature where users are allowed to adjust the price of the food that the AI gave. Incorporating this feature would definitely make my app more accurate and more valuable when tracking the amount of food waste generated in certain places.

### 2.3. Data Collection

A challenge I'm experiencing is data collection. I want the data collected to be insightful, and to provide for meaningful changes. I don't just want to collect the total and sub costs of all the foods, but rather include a summary table that clearly identifies and compares all the individual elements of food waste collected over a period of time. This way, the data can show which types of food are being wasted the most, and where dining hall staff should direct most of their efforts to. Additionally, this can identify which types of food are being wasted the least, if students or customers aren't inclined to eat it. This can also serve as a profit maximization strategy for restaurants or cafeterias, determining the foods that people like to eat the most or the least.

## 3. SOLUTION

The program takes a picture of food trays and through image recognition, object classification, and data analysis, returns valuable data that users of all sorts could utilize to minimize their food waste. Firstly, the program is fed a picture of a plate from the user after a meal. The plate could consist of waste ranging from just scraps to whole pieces of food going to be thrown out. The artificial intelligence engine, Google Gemini, then detects individual components of different food groups, distinguishing between types of food. After it has classified the type of food shown, it provides an estimate on how much food is left on the plate, measuring in typical serving sizes set by the FDA. The AI engine will also return the cost of the different food categories, determining them based on their current USDA market price and the amount of food left on the plate [10]. Finally, the program will return to the users all the types of food that they are wasting, as well as the sub costs and total cost of the individual components. This data can be interpreted by various groups of people, including restaurant or cafeteria staff, financial advisors, as well as the people eating the food. For consumers, it provides an awareness in terms of monetary value of the food that they are wasting, allowing them to make a conscientious effort to minimize their waste. For restaurant staff and financial advisors, the data shown to them should identify trends as to foods that are wasted the most versus those that aren't. It can help them make better fiscal decisions regarding how they can most efficiently allocate their resources, which should also have a positive impact on efforts to conserve food.

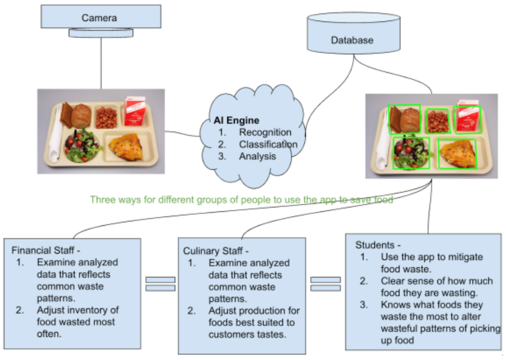


Figure 1. Overview of the solution

A component the program uses is Google Gemini, as an artificial intelligence engine that executes the object classification and data analysis on the images of food waste being fed to the program. It is the backbone of the program, highly accurate in identifying the individual components of food on the plate, as well as being able to estimate serving sizes and provide precise costs.

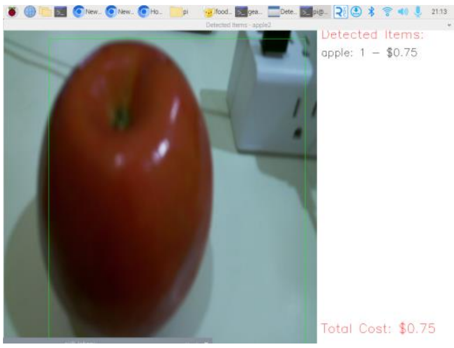


Figure 2. Detect picture

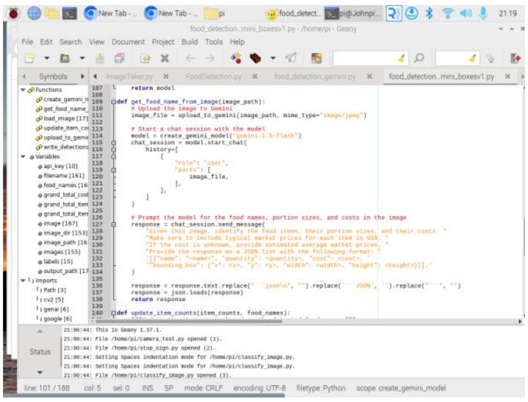

Figure 3. Screenshot of code 1

Firstly, the method on line 109 retrieves a photo (of a food tray) and uploads it to the gemini model following the image path. Then, much like using google gemini online, we give the gemini model prompts to follow. We see that currently we are asking Gemini to return the types of food items, their portion sizes, and their costs. It is very important to be specific when inserting prompts into Gemini, as it determines the quality of the data that we receive. Gemini estimates the portion size, and then using standard market prices for a serving, provides a rough price for the food.

The final step of the program involves different people being able to interpret the summary statistics provided by the program and utilize those statistics to their advantage. By providing total and sub costs for each meal wasted, as well as a grand total cost for all the food waste monitored by the program, users can track their progress or identify weaknesses where waste happens the most, and work to fix it.

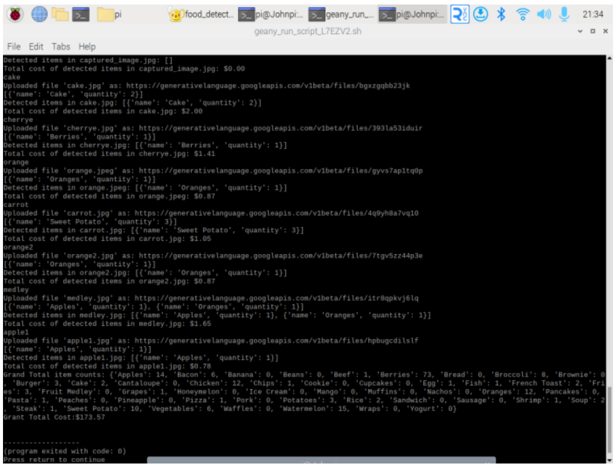

Figure 4. Screenshot of the files

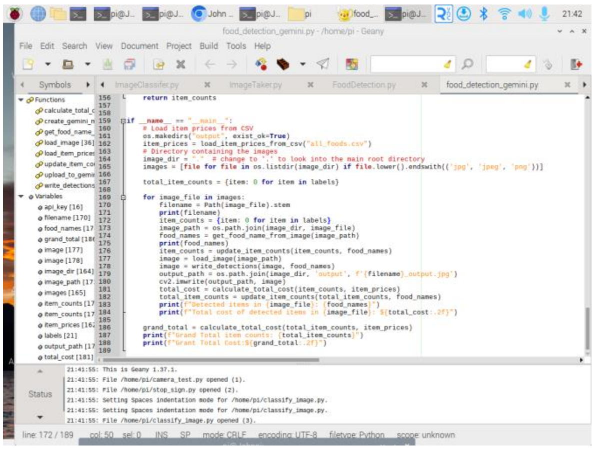

Figure 5. Screenshot of code 2

Another critical component of the app is the Summary Statistics Generator. This component consolidates all the data collected, including food waste types, portion sizes, and costs, into a comprehensive summary table. It enables users to easily visualize trends and make data-driven decisions to reduce waste and improve resource allocation.

```python
class SummaryStatisticsGenerator:
    def __init__(self):
        self.food_items = []  # List to store food items and their costs

    def add_food_item(self, name, portion_size, cost):
        # Adds a food item to the list
        self.food_items.append({
            'name': name,
            'portion_size': portion_size,
            'cost': cost
        })

    def calculate_sub_costs(self):
        # Calculate sub-costs for each food item
        sub_costs = {}
        for item in self.food_items:
            if item['name'] in sub_costs:
                sub_costs[item['name']] += item['cost']
            else:
                sub_costs[item['name']] = item['cost']
        return sub_costs
```

```python
    def generate_summary_table(self):
        # Generates the summary table
        summary = []
        total_cost = 0
        sub_costs = self.calculate_sub_costs()

        for name, cost in sub_costs.items():
            summary.append({
                'Food Item': name,
                'Total Cost': f"${cost:.2f}"
            })
            total_cost += cost

        summary.append({
            'Food Item': 'Total Waste Cost',
            'Total Cost': f"${total_cost:.2f}"
        })

        return summary

    def display_table(self):
        # Displays the summary table
        summary = self.generate_summary_table()
        print("Food Waste Summary:")
        for row in summary:
            print(f"{row['Food Item']}: {row['Total Cost']}")
```

Figure 6. Screenshot of code 3

The Summary Statistics Generator processes all the data collected from user-submitted images and organizes it into an easily digestible format. The code runs after all individual food items on a tray are identified and their costs calculated. It aggregates this data into a summary table that includes total and sub-costs for each type of food wasted.

Key methods include:

calculateSubCosts(): Computes the cost of each food item based on portion sizes and USDA pricing.

generateSummaryTable(): Aggregates sub-costs and calculates the total cost for all meals analyzed.

displayTable(): Formats and displays the summary table in the app’s UI.

These methods ensure accurate tracking of waste and provide actionable insights. By presenting data in a clear and concise manner, users can quickly identify waste trends and areas for improvement, empowering them to take targeted actions to minimize food waste.

# 4. EXPERIMENT

## 4.1. Experiment 1

A potential blind spot in the program is the accuracy of the AI model in detecting and classifying food components. Ensuring accuracy is vital to provide reliable cost estimates and waste statistics.

To test the AI model’s accuracy, we will create a smaller dataset of labeled images, using 100 images split evenly across well-known (e.g., bread, rice) and less common food items (e.g., tofu, quinoa). The model's classifications will be compared against these labeled images, measuring precision and recall metrics. This controlled experiment allows for a focused evaluation without requiring a large dataset. Images for the test will be sourced from the USDA Food Image Database, ensuring consistency and relevance to common food items. By analyzing the results, we can pinpoint areas for improvement in the model’s classification accuracy.

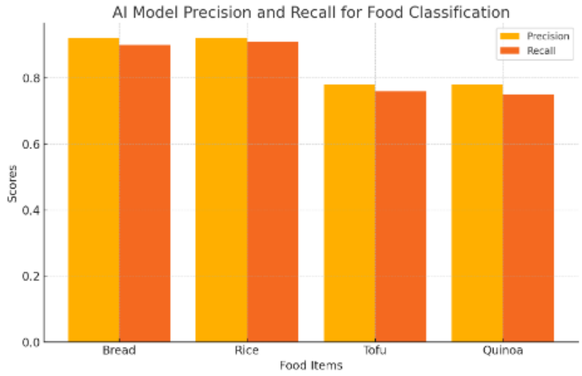


Figure 7. Figure of experiment 1

The experiment revealed a mean precision of 87% and a recall of 84% across the 100 test images. Well-known items such as bread and rice showed a high precision rate of 92%, while less common items like tofu and quinoa were less accurate, with precision at 78%. The median precision was 85%, and the lowest accuracy was observed in the less represented items. The results indicate that while the model performs reliably with familiar foods, it needs improvement in recognizing less common items. Expanding the dataset with additional images of underrepresented food items could enhance the model’s robustness. The better-than-expected performance with certain less common items, like quinoa, suggests that distinct visual characteristics can aid classification, though a larger, more varied dataset will be essential for further improving classification accuracy.

## 4.2. Experiment 2

Another potential blind spot is the accuracy of cost estimation based on regional food prices. Ensuring accurate price calculations is essential for users to trust the app's financial insights.

To test the accuracy of cost estimation, we will compare the AI-generated costs of 50 food items against actual market prices from two distinct regions. The test dataset will include both staple items (e.g., rice, bread) and region-specific items (e.g., tofu in urban vs. rural markets). The experiment will calculate the mean difference between AI-estimated and actual prices. Control data will be sourced from USDA and local grocery store data to ensure accuracy. This will help evaluate the model’s effectiveness in estimating costs across different regions and identify any discrepancies.

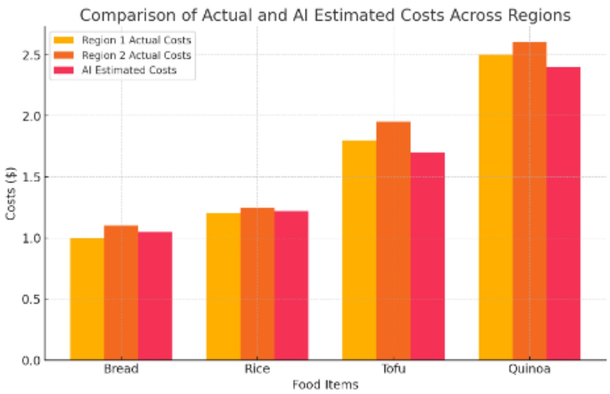


Figure 8. Figure of experiment 2

The experiment showed a mean cost deviation of 5% for staple foods and 12% for region-specific items. The median deviation across all items was 7%. Staple items like bread and rice exhibited lower deviations, with less than 3% difference in both regions, demonstrating the model's high accuracy for common items. However, region-specific items like tofu displayed a larger deviation, up to 15%, due to regional price variability. The findings highlight the need for users to input local price adjustments for improved accuracy. These results confirm that while the model is effective for generalized costs, incorporating a feature for user customization of prices could significantly enhance its reliability, particularly for regionally diverse items. This experiment underscores the importance of adapting the app's cost estimation logic to cater to varying market conditions.

## 5. Related Work

A study by Onyeaka et al. (2023) explores how artificial intelligence can be leveraged to combat food waste while promoting sustainability within the circular economy framework[11]. The research highlights AI's role in monitoring and optimizing supply chains, redistributing surplus food, and minimizing resource inefficiencies. It demonstrates that AI-driven interventions can significantly reduce waste at multiple stages of food production and consumption. However, the study acknowledges limitations, such as high implementation costs and the need for extensive data to train AI models effectively. Unlike this approach, our project focuses on empowering individual consumers by providing real-time cost estimations and waste tracking through an accessible mobile application, thereby encouraging direct behavioral change.

Sigala et al. (2024) examined the implementation of an AI-based waste-tracking system in the Horeca (Hotels, Restaurants, and Catering) sector [12]. Their system automatically records food waste, providing actionable insights to reduce excess production and improve inventory management. The study demonstrated substantial reductions in food waste, showcasing the effectiveness of AI in commercial settings. However, the solution's dependency on large-scale infrastructure and its limited focus on end-user behavior are notable drawbacks. In contrast, our project addresses these gaps by targeting individual users directly, enabling them to monitor and reduce their food waste through personalized insights, which enhances its adaptability for both commercial and personal use.

Nu et al. (2024) explored the impact of AI in reducing food waste within commercial kitchens by deploying a system that digitally tracks discarded food items [13]. Their findings indicate that AI significantly enhances inventory management and reduces food waste by identifying inefficiencies in real time. However, the system's effectiveness is limited by its reliance on kitchen staff to consistently input data and its focus on commercial environments. Our project improves upon these limitations by automating the data collection process through image recognition and providing cost insights directly to individual users, thus expanding its application beyond commercial kitchens to everyday consumer behavior.

## 6. Conclusions

While our project demonstrates significant potential in reducing food waste, several limitations remain. One notable challenge is the reliance on image recognition technology, which may struggle with inconsistent lighting or ambiguous food presentations, leading to occasional misclassifications [14]. Additionally, the app's cost estimation accuracy can be affected by regional price variations, which may limit its effectiveness without user input for adjustments. The model's performance with less common or culturally specific food items is another area for improvement, as it relies heavily on the diversity of the training dataset.

Future improvements could include expanding the training dataset to encompass a wider variety of food items and conditions, integrating dynamic pricing models based on real-time market data, and enhancing the app's user interface to provide more intuitive guidance [15]. Additionally, incorporating machine learning feedback loops from user corrections would improve accuracy over time, making the app more reliable and effective for a broader audience.

In conclusion, our app offers a practical, AI-driven solution to combat food waste by providing users with actionable insights into their consumption habits. By leveraging technology to promote behavioral change, the project highlights the critical role of individuals in reducing waste, fostering sustainability, and contributing to global efforts to address food insecurity.

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