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Recipe Recommendation System Using IoT-Based Food Inventory Management of Perishables for Household Food Waste Reduction

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One of the most pressing worldwide issues is food waste. Food waste has increased dramatically as a result of population growth, fast urbanization combined with industrial development, and changes in lifestyles and economic positions. The study aims to develop a food inventory management and recipe recommendation system for perishable items stored in the refrigerator to lessen the food waste generated within a household. The system consists of a camera module, load cell, Raspberry Pi microcomputer, and a mobile application. The automatic addition of perishable items uses Convolutional Neural Network (CNN) for classifying fruits and vegetables through transfer learning method. Milk and meat products are manually added to the inventory. The mobile application is used for viewing the inventory, expiration of perishable items, and recipe recommendation. The recipe recommendation is based on the expiration and availability of perishable items to reduce household food waste. According to the gathered data, the precision of different classes of the fruit and vegetable model ranges from around 71 % up to 80 % in terms of its recall values, while the accuracy of the model is evaluated at 74 %. The recipe recommendation system was able to fully utilize the recorded perishables roughly 81 % of the time. For food waste reduction, a daily average of 108.4 g of perishable food waste, including food peels, leftovers, and expired ingredients, has been reduced to 71.53 g, which accounts for about a 30 % decrease. The results show how the recipe recommendation system contributes to reducing household-generated food waste.

1. Introduction

Food wastage is an emerging global crisis that is affecting not only the physical health of the earth but as well as the population that inhabits the entire planet. The Food and Agriculture Organization (FAO) of the United Nations (2019) defines food waste as "the decrease in the quantity or quality of food resulting from decisions and actions by retailers, food service providers, and consumers." Roughly around one-third of the food produced for human consumption every year, approximately 1.3 billion t, gets lost or wasted.

The case in the Philippines is not different. According to the World Wildlife Fund–Philippines (2020), it is estimated that around 2,175 t of food scraps in greater Metro Manila alone are thrown in the garbage every day in the year 2020, while around 308,000 t around the country are being considered as food waste. Experts from the FAO emphasized that one of the major reasons contributing to food wastage is the lack of planning on the side of the consumers. People tend to buy lots of food without planning when and how these foods will be prepared for consumption. After some time, they fail to remember using or preparing the food they bought. It is a terrible fact that there is a large amount of food being wasted while a large portion of the world suffers from hunger and malnutrition (Närvänen et al., 2019).

A new study conducted by the UN Environment Programme between homes, restaurants, and food stalls, about a third of food being produced never reaches the mouth. Food waste occurs at the household consumer level in about 40 % to 50 % of cases (UN Food programme, 2021). In Manila alone, nearly 2,000 t of food are thrown away or put to waste daily. According to the study published by the UN Environment Programme during the year

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2020, each household tosses food waste that consists of about 30 % on meat, fish, and poultry products, 25 % fresh fruit, 22 % fresh vegetables, and 11 % dairy products such as milk and eggs. This is a major problem considering that one out of three Filipinos lives below the poverty line. In fact, it is estimated that about 30.7 % of Filipinos, or 7.6 million families experienced starvation during the pandemic simply because there was not enough food to eat. According to a study by the World Wildlife Fund–Philippines' Brian Roe, "People eat a lot less of their refrigerated food than they expect to." From their survey, participants expected to consume 97 % of the perishable goods in their refrigerators but really finished only about half.

Several research and studies are conducted with the sole purpose of identifying the best ways or methods to lessen the amount of food waste around the globe. One effective method is through the utilization of instructional language generated by computers. One of the suitable examples of instructional language is cooking recipes. According to Schanes et al. (2018), cooking using recipes based on what is available at home is an effective strategy to prevent food wastes. Cooking recipes are a very specific type of text, which allows the sharing of culinary ideas between people by providing an algorithm for their realization. Following a certain recipe may help reduce the amount of food waste generated because consumers would be able to know the exact amount of ingredients needed to prepare a certain dish. Each recipe also considers the number of servings it can offer thus preventing consumers from cooking too much food while enhancing their cooking skills regarding precise portion control (Graham-Rowe et al., 2014). The problem with cooking too much food is that it often produces leftovers and people often forgets about the leftovers and most of the time, it ends up in the trash. There are also recipes that focus on preserving foods to extend their shelf life.

Households are considered the source of the majority of all food waste. Food waste has been the underlying problem that is wreaking havoc on the environment, from resources taken up for food processing to the container of expired and unusable ingredients that releases greenhouse gasses as it decomposes in a landfill. Food wastes have environmental impacts and have no benefits to society. According to various studies, the environmental effects of household food waste that ends up in landfills produce a huge quantity of methane, which is a considerably more potent greenhouse gas than carbon dioxide (CO_2), causing global warming and climate change (Herrero Garcia et al., 2018). Studies are being conducted to minimize, recycle, and manage food or solid waste. According to Herrero Garcia et al. (2018), household food waste is a great source of raw material by converting the biodegradable compound to volatile fatty acids (VHA), lactic acids, and others. A similar study done by Lauri et al. (2021) suggests recycling urban organic waste using acidogenic fermentation to recover VHA. An alternative solution to manage organic waste is by applying microorganisms to expedite the composting process (Leow et al., 2018). The related studies require a complicated process, equipment, and a certain amount of food waste before a usable end product is produced. Even with the technology that is present today, there are still limited resources available that would provide instructions on how to reduce the food waste generated within one's household. Furthermore, the ongoing pandemic and high inflation also affected the supply of the food stock within an individual's home which led to having a low amount of food stock within a household which made it difficult to determine what to cook with only the given limited ingredients. Each household also wants to maximize what's left in their refrigerator.

The study provides users recipes from different Filipino recipes focusing on viands, with the available ingredients on hand to lessen the food waste crisis in the country. The study aims to develop an inventory management system with an integrated recipe recommendation application for perishables. The system is limited only to perishable ingredients which were considered fresh and are commonly found in refrigerators, such as meat, eggs, fruits, and vegetables. The system will automatically identify fruits and vegetable using image processing and stores them in the database. Meat products such as pork, chicken, beef, fish, and many others will be manually classified but will be weighed automatically using a load cell. The inventory will be updated whenever a product was used for a recommended recipe. The expiration of perishable ingredients will be automatically listed in the database, which is based on its average shelf life as stated in different research and studies. The system will require the user to reweigh the ingredients used to update the inventory system.

2. Methodology

A system diagram is a method to describe a system that exists or needs to be built (Di Scala, 2019). Figure 1 depicts the system diagram, which describes the system's overall structure and flow of data. Initially, recipes from various websites will be extracted and pre-processed accordingly into a structured format for the system to evaluate. This involves recipe data which includes its recipe ingredients, serving units, and serving amounts. The researchers focused on a website recipe from kawalingpinoy.com that manages Filipino food recipes. The mobile application is used to manage the inventory and view the recipe recommendation. Besides the application, a camera module is available for the system to be its tool for registering or configuring an item conveniently. It uses an image capture from the camera module with the given object item for image classification. As for the weight data, it is obtained with the load cell. The camera is designed to be on top of the ingredient to have an appropriate view angle and increase the chance of the item being recognized. The system will use a Raspberry Pi 3 microcomputer to act as a data sender or a tool for the overall system. It will be the one who will process the image capture and decode the perceived module data into the databases.

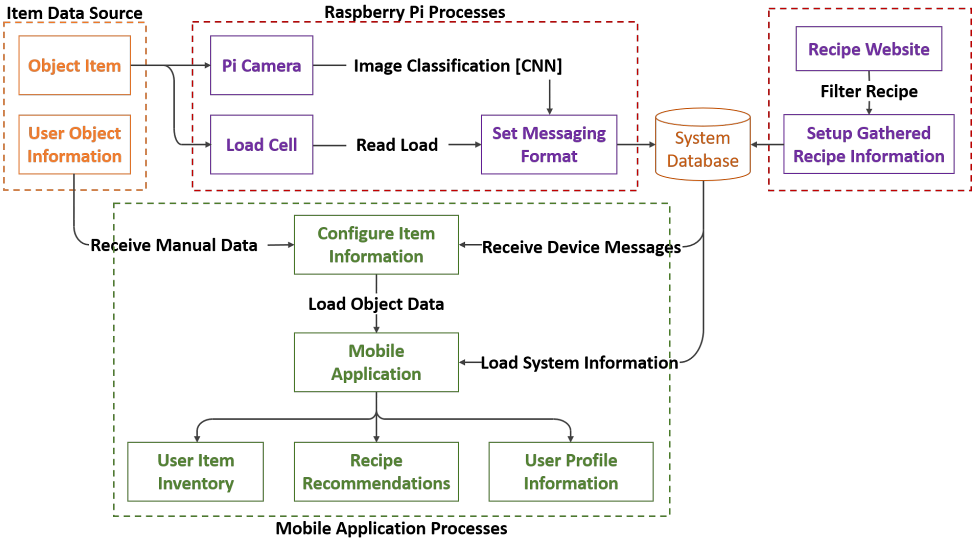

Figure 1: Architectural Design

2.1 Mobile Application and Prototype

The initialization application starts with the user login, account registration, and forgot password scenario as shown in Figure 2a. It is required to have a registered account before the user can use the inventory management and recipe recommendation system.

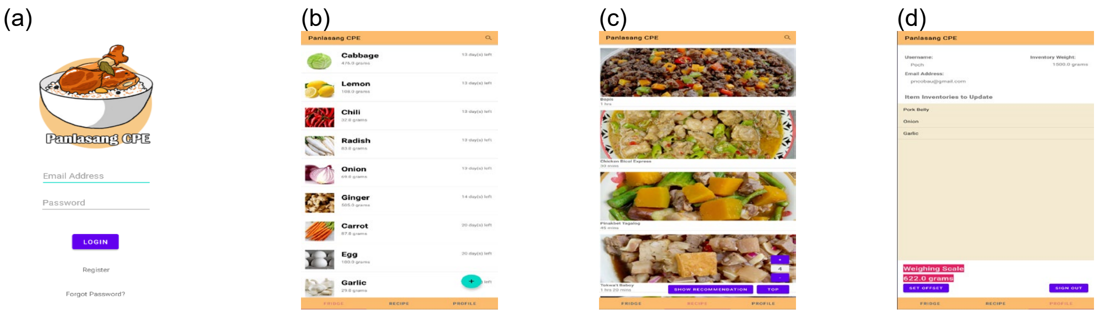

Figure 2: Mobile Application's (a) Login page, (b) Fridge Menu, (c) Recipe Menu, and (d) Profile Menu

There are menus in the mobile application, namely: Fridge, Recipe, and Profile. The Fridge Menu is used for managing an inventory such as add, delete, search, and update inventory items as shown in Figure 2b. This inventory list will sort its inventories by their expiries in ascending order after being loaded up. A search engine can be used by the user when looking for a specific ingredient. Selecting an item will show the item expiration, item name, and item amount total in grams. If the item has an expired amount, it will be deemed to be deleted. When updating an amount, the system will ask for the weight of the item using the load cell. The Recipe Menu allows the user to browse for a recipe, cook a recipe, and even request for an optimal recipe to cook at the moment as shown in Figure 2c. The recipe list from the recipe tab has two modes of previewing its list. First is by default, the system will list down all the recipes available in the database without any conditions. If the user desires to request an optimal recipe to cook at the moment, the system will make use of the user's inventory and the inputted serving count. These data will help compute recipe scores that can be used for identifying the top five highest score values. After selecting a recipe, the system will display the recipe's name, description, ingredients, and serving count. If they desire to cook the recipe, they can simply click the cook now button, and instructions to guide the user will be displayed. After the actual cooking is done, the user will prompt the system to proceed to the next step. The next step is for the system to know whether there are inventory items needed for the update. If it does not have one, the system will record used inventory items from all of the recipe ingredients and list it all on a list view. In this sense, the user will later know which ingredient is used and needs

to be updated. If there are items needed to be updated, the system will not let the user pass the done cooking process. In the Profile Menu shown in Figure 2d, the user can see their profile information, such as their username, email, and inventory's total weight. All inventory items that need updating and were in cooking a recipe will be displayed here.
Figure 3 shows the prototype design, which consists of a microcomputer, a camera module, and a weighing scale made up of a load sensor, and an acrylic disc. It has a dimension of 30 cm in length, 15 cm in width, and 15 cm in height. The acrylic disk is 10 cm in diameter, and a load sensor which can handle up to 10 kg.

Figure 3: Prototype Design

Image classification is the process of a computer analyzing an image and determining which 'class' it belongs to, such as 'fruit' and 'vegetables'. Convolutional Neural Network (CNN) is utilized for this project since it is effective in decreasing the number of parameters without sacrificing model's quality. The fruits and vegetables image classification model were trained under Keras using the EfficientNetB3 as the base model, through the method of transfer learning. This means that the weights of the EfficientNet model were reused and integrated since this pre-trained model was already intended to be utilized mainly for image classification of different objects within the environment, which comes to more than 1,000,000 images for 1,000 categories.
A balanced dataset means that the distribution for each class is approximately the same which prevents it from being biased to one class (Hvilshøj, 2022). It ensures that evaluation metrics reflect the model's true performance in all classes (Brownlee, 2021). It may introduce some bias but due to time constraints and hardware limitations, the proponents were only able to include 3,000 images of 16 different fruits and vegetables. The precision is calculated by dividing the True Positives by the sum of the True and False Positives. The recall is calculated by dividing the True Positives by the sum of the True and False Negatives. The accuracy was determined by the sum of True Positives and True Negatives divided by the sum of the True Positives, False Positives, True Negatives, and False Negatives.

2.2 Recipe Scoring Algorithm

Eq (1) to Eq (3) shows the tallied ingredient recipe evaluation that was used for Recipe scoring and recommendation. It considers the availability and expiration of the ingredients in the inventory.

$$\sum_{i \in PRI} i = \left(\frac{Expiry-DateGap}{Expiry} + \frac{InventoryAmount}{RecipeAmount}\right)\Big/_{2} + (Tally_1) + (Tally_2) + \cdots \quad (1)$$

$$\sum_{i \in NPRI} 0.2f = 0.2f + 0.2f + 0.2f + \cdots \quad (2)$$

$$RecipeScore = \frac{\sum_{i \in PRI} i + \sum_{i \in NPRI} 0.2f}{|PRI| + |NPRI|(0.2f)} \quad (3)$$

DateGAP is the difference between the actual date of expiration with the current date in days. PRI is the set of all tallied perishable recipe ingredients, and NPRI is the set of all tallied non-perishable recipe ingredients.
The Expiry Relevance Score part of the formula measures the relevance of the item which helps distinguish whether an item will expire soon or not. The value returned will range from 0 to 1. Values that are near to 0 only mean that it is far from being expired, while on the other hand, obtaining values near 1 means that the item will soon expire. This is relevant to the formula as this explains the relevance of the item in terms of its expiry in the current moment. The Amount Relevance Score will return values ranging from 0 to 1, which will explain how the amount of current inventory item is relevant over the given recipe ingredient. The returned values aim to distinguish whether an item is enough to be used or not. Recipe ingredients pertains to an item required from a recipe where each recipe ingredient will be fractioned out with the given inventory item's amount. Values near 0 mean that the amount available from an item is not enough for it to be used, while if it is near 1 only means that an item is near enough to be used. The Recipe Ingredient Tally are tally computed from each recipe ingredient which is used for obtaining the recipe score when summed up. There are two kinds of tallies: perishable and non-perishable tallies. Tallies are scores given to a recipe ingredient that considers the user's

inventory with its amount score and expiry score. This makes perishable tallies have a maximum value of 2 from 0, and non-perishables have a default value of 0.2. The default value of 0.2 is predetermined based on how non-perishables are not appraised in the study. To review more about the whole formulation, the expiry score is merely just an extra value that gives an additional boost when an item is getting expired. This makes the max value of 1 from the amount score the main value. Given this, it is predetermined by the researchers for the non-perishable tally to have the 20 % of the main value hence 0.2.

The collected perishable and non-perishable tallies are then summed up to be used on dividing with the recipe’s max possible total tally. Summing up the tallies is applied to describe the ingredients that a recipe has. It explains the ingredient’s amount, expiry, and the ingredient itself. The max possible tally from a recipe is obtained by summing up the cardinality of perishable recipe ingredients and non-perishable recipe ingredients multiplied by 0.2. Through this, Eq(1) to Eq(3) will also consider the adequacy of a recipe and scoring it accordingly.

3. Results and Discussion

The testing for food waste reduction was conducted in three households. Each household tested the prototype for 10 days and collected data the end of the day. Due to the time constraints and lockdown, the proponents were only able to gather data from 30 respondents to represent a small street community for testing the utilization of inventory using the recipe recommendation algorithm. A Likert scale questionnaire was also provided for the same respondents in order to test the usability of the mobile application.

A satisfaction rating of respondents with the suitability of dishes recommended based on the perishable within the inventory feature of the app was conducted. Seventy percent of the respondents were satisfied while 26.7 % were strongly satisfied with how the application functions as a whole. A mere 3.3 % are neutral.

In every instance of an inventory, the recommendation system helped the researchers identify all the possible recipes to be made with the aid of their respective recipe scores. Recipe scores greater than or equal to 0.75 will be considered adequate. All adequate recipes will be then totaled by their recipe ingredients and will be used for dividing with the total amount of the user's inventory. Through this, the utilization rate done by the recommendation is computed. The application recorded 30 different instances of inventory from different household respondents, which they have provided their data entered in the inventory system. The mean effectivity rate of the recipe recommendation algorithm in utilizing different perishable ingredients within the inventory of each respondent’s household was computed, resulting in fully utilizing the registered perishables by recommending Filipino recipes 81 % of time.

Data was gathered with two different scenarios, one is using the device, and the other is without the device. For both scenarios, the total weight of inventory (TWA) before and after cooking, and total food waste (TFW) were collected on that particular day. Table 1 shows the result after performing paired t-test with the data. The significance level is $\alpha=0.05$, and the critical value for a two-tailed test is $t_c=2.045$. The rejection region for this two-tailed test $R=\{t:|t|>2.045\}$. Since it is observed that $|t|=2.125>t_c=2.045$, it is then concluded that the null hypothesis is rejected. Using the P-value approach: The p-value is =0.0423, and since $p=0.0423<0.05$, it is concluded that the null hypothesis is rejected. Therefore, there is enough evidence to claim that the population before is not equal to after, at the $\alpha=0.05$ significance level.

The dataset for the image classification contains 3,000 images of 16 different fruits and vegetables, which was split into training and test set. The training model contains around 150 images per class while the evaluation is performed on the test set that contains around 15 images per class. A normalized confusion matrix was used to interpret how well the model predictions perform using a fitted model.

The precision ranges from 71 % to 80 %, while recall ranges from 64 % to 82 %. Accuracy results in 74 % which, according to Allwright (2022), is considered good but needs improvement to be considered very good. It has the ability to find all the relevant cases within a dataset as well as identifying only the relevant data points.

Table 1: Paired T-test with Data

	Mean	Std. Deviation	n	95 % Confidence level of the difference		t	df	P
				Lower	Upper			
Without Prototype	0.017	0.021	30	0.01329	0.000253	2.125	19	0.0423
With Prototype	0.011	0.009						
Difference	0.007	0.017						

4. Conclusion

During the conduction of results and data of the research, the researchers initiated to get the correct leading values to meet the objectives that needed to be performed. A recipe scoring algorithm was developed with the

purpose of determining the most optimal recipes to be suggested to the user that will fully utilize the stored perishable items of a single household. According to the gathered data, the recipe recommendation system proposes Filipino recipes that fully utilize the recorded perishables in the inventory roughly 81 % of the time.
Given that the prototype is working as intended, the researchers then tested the device on different households, with people in charge of cooking for each one as its user, to further identify the effectiveness of recommending recipes with an inventory system in reducing perishable food waste.
Analyzing and evaluating the results gathered from the 10-day testing of before and after the utilization of the prototype in each household shows that there were different factors that contributed to food waste that was addressed by the prototype. Households accumulate an average of 108.4 g of perishable food waste daily without using the device and 71.53 g when the device is being utilized. According to the observation made during prototype testing, there is a correlation between the use of proper serving amounts, inventory system, and recipe recommendation, and the decrease in daily food waste. This means that according to the gathered data, it is concluded that there is a significant difference between the food waste generated within a household with and without the use of the prototype.

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