Utilizing Machine Learning to Create an Effective Tool for Managing Food Waste

Grant Proposal

Rohan Gulati

Massachusetts Academy of Math and Science

85 Prescott Street, Worcester, MA

Author Note

If needed, write notes here with an indented first line. Be mindful, the text in your lit. review should be between 10-12 font size with a chosen font of Caibri, Times New Roman, or Arial. A Table of Contents is *optional*; however, you should format the section headers appropriately to have them show up in the TOC. Lines should be double-spaced.

Executive Summary (Eng)

The abstract would contain an overall summary of what you (as the author) would like to convey. It would include some of the knowledge gaps that would eventually lead to researchable questions you have identified in the field.

Keywords: emotion understanding, interest, social development, prosocial behavior, infants

Utilizing Machine Learning to Create an Effective Video Tool for Managing Food Waste in Refrigerators

Food waste is a significant issue affecting the global economy, human health, and environmental elements (Chigurupati et al., 2025). More specifically, over one trillion dollars' worth of food goes to waste every single year, instead of being used to address the hunger of 782 million people worldwide (Gravert & Mormann, 2025). Furthermore, this issue impacts the spread of disease, with 200 diseases sprouting from the consumption of spoiled food, affecting 4 billion individuals per year. These diseases can be detrimental, resulting in 1.6 million fatalities attributed to food contamination (Chowdhury et al., 2025). Additionally, food waste affects the environment due to the release of methane and other greenhouse gases during the production process, causing resource inefficiency (Reddy et al., 2025). Currently, a prevalent issue is the wastage of food before and after the sales process, which contributes 60% of the total food waste (Gravert & Mormann, 2025). With the countless effects stated and a clear outline of when the errors occur, one can create predictions on the root cause of the problem. A common cause includes the human dependency for detecting food waste, which leads to large expenses while being unreliable (Chigurupati et al., 2025).

Storage Disorganization

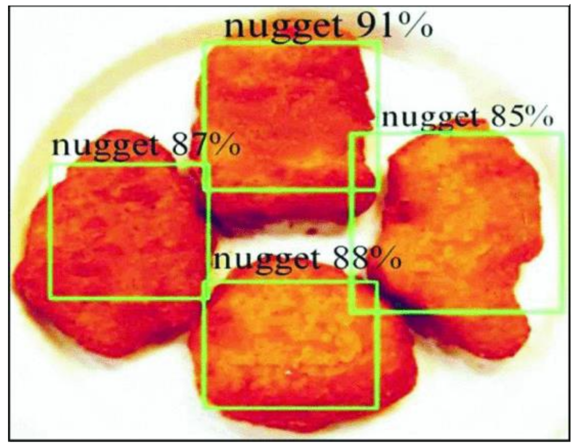
This problem is especially prevalent in urban households with busy storage locations, such as packed refrigerators. With the amount of food available, storage in such areas can often be disorganized, leading to items being forgotten and eventually spoiling. Often, to prevent such issues from occurring, households manually record the items inside their refrigerators and the time they were stored. However, this method is extremely time-consuming and often results in the subject forgetting to record the item. Current automatic methods are either unable to identify a variety of food, struggle to identify any sort of spoilage, or require manual inputs from a user for each item. Thus, this creates a need for urban households to have a camera system which detects whether fresh and cooked foods in refrigerators are demonstrating signs of spoilage to reduce the amount of food waste. This project will address various problems including the lack of surveillance of food in refrigerators and their eventual spoilage due to the lack of reminders for usage. It will also include solutions to the problem of inaccurate prediction systems and lack of flexibility in product type for such products.

Technology Procedures

To create an automated system to identify spoilage in foods, especially fresh produce, certain technology should be implemented, and specific procedures must be executed. To identify the product in a crowded, real word scenario, bounding boxes and image segmentation are necessary. Once the confidence for an image corresponding to a certain class has reached a threshold, an image can be taken (Baby Shamini et al., 2023). Figure 1 shows how a bounding box can be used to identify and analyze separate items in an image.

Figure 1

Image of bounding boxes and the confidence of predictions



Note. From Baby Shamini et al. (2023).

Data Preparation

Data preparation consists of many steps including locating/recording the data, formatting it properly, and then dividing it into categories. Firstly, any model must have access to accurate data, and then the data must be formatted to be congruent and applicable to the specific model. Lastly, after the storage step, the data must be divided into testing, validation, and training data, often with a ratio of 7:2:1 (Wang et al., 2021). This ratio allows for sufficient training data, while allowing predictions for both validation and testing. Often, there may not be enough data available, leading to the necessity for data augmentation. Data augmentation involves slightly altering an image and adding it to the dataset to expand the dataset which the model uses to train and test. Some alterations include rotations, slightly changing the color, reflections, translations, and adding speckles.

Deep Learning Model

After the data is prepared, the Convolutional Neural Network (CNN) model may be constructed and used for training. As Figure 2 shows, the CNN model is made of five main types of layers, including the input layer, convolutional layers, pooling layers, flattening layer, and dense layer. The input layer is used to confirm that the images are formatted correctly and consistent throughout the model. The convolution layers identify the patterns, with each subsequent layer identifying more complex and succinct patterns. For example, initial layers might identify edges and color, while further layers may analyze spot spoilage and wrinkles. After each convolutional layer, there is a pooling layer, which is used to summarize the most important findings in a specified area grid. Flattening layers convert the two-dimensional maps into one-dimensional lists, so that the dense layers can make the final decision on what category an object is. Often, a dropout layer may be used to ignore certain patterns to prevent overfitting and allow generalization (Chowdhury et al., 2025). A dropout layer ignores a percentage of the patterns it is learning, hoping to identify only re-occurring patterns. Within these models, many variables, known as hyper-parameters, must be constantly adjusted by the trainer. Some important hyper-parameters include the model's learning rate, the number of epochs(iterations) through the dataset, and the dropout rate (Chigurupati et al., 2025).

Figure 2

Model of the layers of a CNN model

Note. From Chowdhury et al. (2025).

Through such methods, one can create a system which can detect patterns, such as spoilage, and use it to act. In this case, these procedures will be used to prevent food waste and allow for a more efficient storage system.

Section II: Specific Aims

This proposal's objective is to describe a system capable of storing what items are inserted into refrigerators and tracking when they will expire.

Our long-term goal is to limit the amount of food waste in all households where the central hypothesis of this proposal is to create a system that can record the expiration state of all items in the refrigerator and inform a user when they are approaching the deadline. The rationale is that often such items are placed in locations which are difficult to reach and hence, notice. This product will allow for constant reminders to prevent the wastage of those forgotten items. The work we propose here will prevent spoilage of food items in refrigerators for households, helping the environment, food insecurity, and the economy.

Specific Aim 1: Identify food spoilage in common items using visual cues, time of insertion as well as removal, and barcode information

Specific Aim 2: Identify the spoilage of unfamiliar food items through new user data provided through images

Specific Aim 3: Display the state of foods in the refrigerator and possible recipes for spoiling foods through an application

The expected outcome of this work is a system that alerts users of food spoilage occurring in their fridge. This will remind them to use the product in the refrigerator, perhaps on one of the recipes provided, to prevent food waste.

Section III: Project Goals and Methodology

Relevance/Significance

Food spoilage is a major problem, contributing to food waste, costing households billions of dollars every year, and posing a health risk. However, family refrigerators lack any sort of automated tracking system to track the status of the food and its shelf life. This project is a significant step towards a technology located inside a refrigerator which can prevent spoilage, reduce waste, and improve food safety for families.

Innovation

This project is an improvement of the current fridge, using computer vision, barcode data, and time tracking to create a fully automated system which trains itself. Most refrigerators lack any system to track the items inside. If they have the ability, it is often through photos of receipts or for manual inputs for each product. Although many of the aims having already been created to an extent, the focus for this innovation is to combine the capabilities of computer vision, barcode scanning, and time tracking.

Methodology

Project Goals

- Determine whether a machine learning model can accurately identify food items in a refrigerator environment.
- Predict spoilage time through barcodes, visual cues, and time of insertion.
- Display products approaching spoilage and appropriate decisions to make with them through an application.

The methodology highlights every significant section of the project aims. The project outcome will be a system which can detect the condition of a food at 95% accuracy, deciding whether it is spoiled, approaching spoilage, or fresh.

Procedure

- Use an apple as the fruit for the preliminary model
  - Use the Fruits Fresh and Rotten Kaggle Dataset to organize the information into accurate folders for training and identification.
  - Create a CNN model to train with the data from the dataset, focusing on preventing overfitting.
  - For more advanced models, it may be wise to use more complex CNN network structures, like VGG, ZFNet, GoogLeNet(Liu et al., 2016).
- Identify whether certain examples of the product have spoiled with an accuracy of greater than 90% within a training period of 10 days
  - Identify spot spoilage and color changes to predict spoilage
  - Use the barcode or the use-by-date if applicable to predict spoilage
  - Use the insertion and removal time of the product to predict spoilage

  - Combine the 3 situations to identify the most probable class.
- Identify spillage in at least 5 more items for an accuracy of greater than 90% for each within a training period of 10 days for each one.
  - Use the Fruits Fresh and Rotton Kaggle dataset with access to bananas and oranges as well.
  - Allow the model to contain multiple classes and classify each product
- Allow the user to input in full images of new products, provide a label for the product, and get a prediction from the model after 10 inputs with an accuracy of 70 percent.
  - Collect the data and augment to prevent overfitting
  - Create an autonomous system where the model can begin to train itself and adjust hyperparameters until it can predict the new product.
  - Allow the model to make predictions from the information provided and store the learning data
- Display the model through an easy-to-understand application which streamlines the process of checking for food spoilage
  - Create the interface which displays the items present in the refrigerator and their approximate spoil-by-date
  - Alerts the user when the spoilage date is approaching.
  - Provides a user-friendly system to capture images for future predictions with new products
  - Assists in recipe choice through existing recipe AI models. Uses a probe object to identify the amount of food as it is used for volume calculation of food items (Wasif et al., n.d.).

Success Measurement

The project success will be measured by comparing the food recognition accuracy along with the spoilage prediction accuracy.

This project will span for 3 more months, meaning the timeline includes adding as many products as possible to the manual training section, creating a system which learns from input data, and finally testing the product with short term tests. Long term tests are also important, especially in this adjusting model, to identify the improvement after countless hours of training data provided by the user.

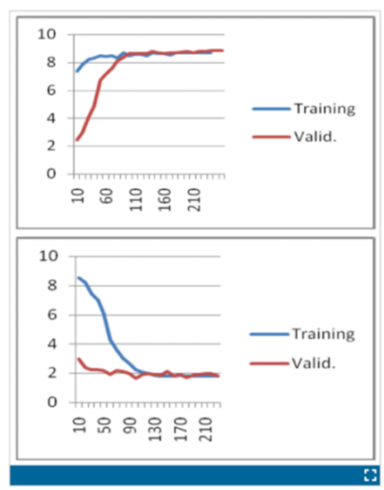
Specific Aim #1:

The device must be able to determine the accuracy with which this CNN model can detect early spoilage indicators in common household produce using visual changes, barcodes, and information about the length of storage. The objective is to build a model which can identify food spoilage in basic products through manual training. Our approach (methodology) is to first find a dataset for the produce, train a convolutional network to identify the item, and then detect signs of spoilage. Using this information along with the barcode and time- since-insertion, a prediction can be made. Our rationale for this approach is that it combines multiple methods to create assurance. One method might work for a specific product, but may fall for other products, meaning that the other methods may be used.

Justification and Feasibility. Using the same type of CNN model, spoilage was identified at a level just below 90% in Figure 3 (Usha et al., 2023). Although her CNN model was not very accurate, it shows good potential for recognizing a wide range of targets, leading to belief in the feasibility. To obtain a dataset, one would need to research certain datasets for spoiled foods, as any machine learning model needs a significant amount of data. To allow for this, data augmentation is necessary, with these "degraded training sets resulting in improved generalization capabilities and enhanced robustness" (Hemavathy et al., 2023). Although the first preliminary model will only identify apples, as more images are found in the data set, it is possible for the model to be extended to other produce. Furthermore, all 3 methods will be used since there is no single method that works well for all foods. Visual cues are strong but often identify the wrong item and need to be meticulously trained. Expiration dates are often difficult to find and many QR codes have stopped working. Using the time of insertion is often useful but may

Figure 3

The training data of CNN model used to recognize the spoilage of items.



Note. From Hemavathy et al. (2023)

be misleading if an item has removed an item and then returned it. Overall, this feasible, redundant format allows for every food to have predictions associated with it.

Summary of Preliminary Data. A CNN model was trained on a dataset with a total of 5038 augmented images of fresh and rotten apples. The training data contained 4039 total images while the test data contained 999 images. The model was comprised of 1 input layer, 3 convolutional layers, 3 pooling layers, 2 hidden dense layers, 1 flattening layer, and one dropout layer. This model was trained for 20 epochs with a batch size of 12. The loss graph from Figure 4 shows a low training loss of 0.0847 and a low validation loss of 0.1594. Both losses are extremely similar, signifying the lack of overfitting. However, the large spike at 10 epochs shows either a lack of data shuffling or a learning rate which is too high. The area under the curve of 0.9913 of the ROC curve from Figure 5 shows that the model can generalize well and constantly distinguish positive cases from negative cases. The misinterpreted images show that the model needs data with more variety in color since most of the false positives were yellow apples. On the other hand, most of the false negatives were for apples with slight blemishes and wrinkles. Therefore, the size of the images should be increased, or the filter size should be decreased. These changes would allow the model to focus more on specific details of the apple instead of generalizing a section.

Figure 4

Epoch vs. Accuracy Graph and Epoch vs. Loss Graph

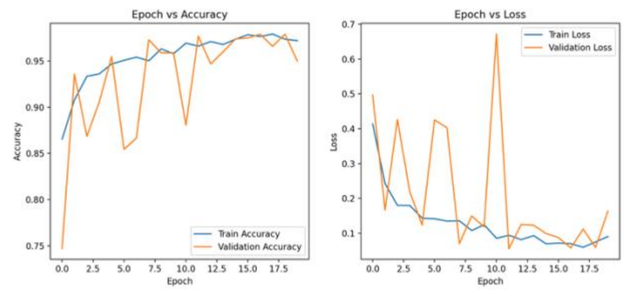
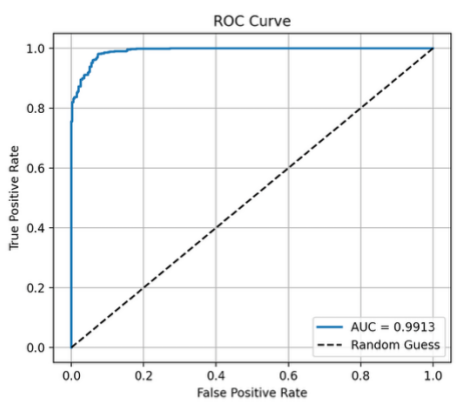


Figure 5

ROC Curve analyzing the sensitivity vs the specificity.



Expected Outcomes. The overall outcome of this aim is to identify spoilage in common items to provide a strong initial model for the user. With a solid baseline of identifiable products, the model should be viable for preliminary testing through real products. This knowledge will be used for evidence to prove that this product is viable for initial testing in the field where motion blur and imperfect images play a role.

Potential Pitfalls and Alternative Strategies. We expect that the limited variety may cause the model to misclassify items when in imperfect lighting. If this occurs, we can use the images of misclassified items to add to the training data. Another common problem may be that some items do not show visual blemishing. In these situations, a greater weight can be applied to the time-since-insertion to calculate the time to spoilage. Lastly, a possible issue may be that the model is unable to maintain the same accuracy and lack of overfitting with more classes. In that case, further layers can be added and adjustments to the weights can be made.

Specific Aim #2: **Identify the spoilage of unfamiliar food items through new user data provided through images**

Justification and Feasibility. Most refrigerators contain unfamiliar products that the system has not been trained on. For this device to be applicable in real world scenarios, it must be able to adapt to new products and learn from user data. Without such abilities, the device would be unable to handle the diversity in different cuisines and hence, be impractical for a majority of the world's population. This aim is feasible, as with data augmentation and adjusting the images slightly, the model can slowly learn from images it is given. With constant new images from the user, the model will only get more accurate over time. However, it may be difficult to make predictions of spoilage with training data of un-spoiled items.

Summary of Preliminary Data. Although no data has been collected for the model's self-training capabilities, the apple model provides sufficient evidence that the CNN structure can generalize well. Additionally, the apple model's capability to still recognize altered data provides confidence in its capabilities to recognize real data. The low levels of loss and overfitting from Figure 2 prove that the model has good architecture.

Expected Outcomes. The expected outcome for this system is that it can roughly learn unseen products with an accuracy of 70% after users input 20 images. This percentage could increase especially if images of the unseen product were identified online by the system and used for training. The system can also use the data from users to further train the model for real-world scenarios. This will expand the scope of the dataset allowing for increased accuracy over time and making this project viable longer-term.

Potential Pitfalls and Alternative Strategies. The greatest challenge for training a model with limited data is overfitting. With only 20 data images, it is essential to apply data augmentation and limit the initial layers from saving their weights. Another possible challenge is users providing different labels for the same item, leading to different class names for the same training data. To fix this, one must make the interface use the internet to get all possible names for the provided item to compare with previous logs.

Specific Aim #3: **Display the state of foods in the refrigerator and possible recipes for spoiling foods through an application**

Justification and Feasibility. An application is necessary for this product to allow the user to be notified of possible spoilage, keep track of the items in their fridge, and decide how to use the products. Without such an application, this product would lose a competitive advantage and be unable to communicate with the user. The application interface allows for further personal features for the user, such as personalized recipe suggestion, elevating the system. This application is feasible as it requires to keep track of the items in the refrigerator and push notifications to the user when items are approaching spoilage. The other features are extremely common in other devices which lack the automation of this product.

Summary of Preliminary Data.

Expected Outcomes.

Potential Pitfalls and Alternative Strategies.

Section III: Resources/Equipment

Section V: Ethical Considerations

Section VI: Timeline

Section VII: Appendix

Section VIII: References

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