Advanced Machine Learning — Final Project Proposal

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PROBLEM

Grocery retail is a low-margin industry where every penny matters for profitability. One of the biggest challenges in this business is managing food waste, particularly when it comes to perishable items such as fresh produce. While efficient supply chain management can help reduce the risk of spoilage, it's not a perfect solution. Fresh produce is especially prone to damage or aging during its journey from farm to shelf. Selling damaged goods not only reduces profits but also diminishes customer satisfaction.

To address this issue, grocery retailers can leverage technology that identifies spoiled or damaged produce, allowing employees to remove those items before they reach the shelves. By utilizing a pre-trained foundation model with image recognition capabilities, retailers can assess the quality of perishable products like fruits and vegetables before they are made available to consumers at stores like Whole Foods, HEB, or Target. This approach ensures that only the best produce is offered for purchase, enhancing both profitability and customer experience.

DATA

For this project, we are utilizing a dataset of approximately 30,000 images that include a wide variety of fruits and vegetables, with both fresh and spoiled examples. This dataset has been sourced from Kaggle and contains labeled images for both categories, ensuring we have balanced and diverse data for training and evaluation. The dataset includes commonly perishable produce such as apples, bananas, tomatoes, cucumbers, and more, all of which are critical to our problem domain of spoilage detection. Each image is labeled either as "fresh" or "spoilt," providing a solid foundation for training a binary classification model.

Preprocessing Steps: Each image will be resized and normalized to ensure uniformity across different types of produce. We also plan to split the dataset into training, testing, and hold-out validation sets to ensure a robust evaluation of the model's performance.

*For further details on the dataset (and links to them), please refer to Appendix.

APPROACHES

There are multiple approaches to consider when tackling an image classification problem, but our specific goal is to detect whether a product is starting to spoil by identifying subtle, early changes—not just obvious signs of decay. Achieving this requires both a robust dataset and a well-suited model. Here are the approaches we plan to explore:

Deep CNNs: We will experiment with deep convolutional neural networks (CNNs) like ResNet50, VGG-16, Inception, and EfficientNet, which are well-suited for this task. Additionally, we will explore pre-trained models available on Hugging Face that are trained on data similar to our use case, providing a strong foundation for image classification.

Support Vector Machine (SVM): SVM offers an alternative to CNNs and serves as a valuable comparison. It is highly robust against overfitting, with tunable cost parameters for optimization. Its ability to define class boundaries using only a subset of the training data (support vectors) makes it memory-efficient and effective for generalization.

Open-Source VLMs and Multimodal LLMs: Another approach involves utilizing APIs for vision-language models (VLMs) or multimodal large language models (LLMs). With zero-shot or few-shot prompting, we can build an image classifier and evaluate its performance compared to deep CNNs.

Fine-Tuning Open-Source VLMs: While fine-tuning vision-language models can be computationally expensive, we are considering this for exploratory purposes. Although it's resource-intensive, fine-tuning could enhance our knowledge and improve model performance. We plan to experiment with smaller parameter models available on Hugging Face, such as BLIP-2 and Llava-Next, to see if this approach is feasible for our use case.

By combining these strategies, we aim to develop a highly effective solution for detecting subtle signs of spoilage in perishable products.

APPLICATIONS

Quality Control and Assurance in the Food Industry: Automated systems can play a pivotal role in ensuring the quality of fruits and vegetables by efficiently identifying and sorting fresh produce from spoiled or damaged items.

Reducing Food Waste: By detecting damaged or deteriorating produce early, businesses can significantly reduce food waste. These items can be diverted to composting or sold at a discount before they become inedible, maximizing their value and minimizing waste.

Smart Refrigeration Systems: Incorporating freshness detection technology into smart refrigerators can alert users when items are nearing spoilage, helping individual households reduce food waste by encouraging timely consumption.

Disease Detection in Crops: Early detection of spoilage not only preserves food quality but can also serve as an indicator of potential disease outbreaks in crops, allowing for swift intervention to prevent further contamination.

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APPENDIX

Datasets:

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Dataset Details:

Fresh / Spoilt	**Produce**	**No. of Images**
Fresh	Apple	3215
Fresh	Banana	3360
Fresh	Bitter Gourd	327
Fresh	Capsicum	1269
Fresh	Cucumber	496
Fresh	Orange	1854
Fresh	Potato	806
Fresh	Tomato	2113
Spoilt	Apple	4236
Spoilt	Banana	3832
Spoilt	Bitter Gourd	357
Spoilt	Capsicum	901
Spoilt	Cucumber	676
Spoilt	Orange	1998
Spoilt	Potato	1172
Spoilt	Tomato	2178
	Total	**30357**