Expiry Date Validation AI Project:

Abstract/Introduction:
In retail stores, managing product expiry dates efficiently is critical to minimizing waste and maximizing profitability. This project explores the development of an automated expiry date management system, focusing on decoding barcode and QR code data, Optical Character Recognition (OCR), and manual data entry. While traditional barcodes and QR codes lack expiry date information, leveraging OCR and a structured dataset enables tracking and forecasting. Additionally, machine learning models predict expiry timelines, and recommendation systems facilitate early clearance sales, offering a comprehensive solution to expiry date management.

Literature Review:
Barcode and QR Code Decoding:
Barcode technologies such as EAN-13 and QR codes are widely used in retail for inventory management and tracking but often do not encode expiry information. Studies highlight their potential for integrating additional data storage capabilities.
Tools like Pyzbar and OpenCV are frequently employed for barcode and QR code decoding.
Optical Character Recognition (OCR):
OCR, particularly using tools like Pytesseract, has demonstrated effectiveness in extracting textual data from images. Challenges arise with low-resolution images and noisy text backgrounds.

Machine Learning in Retail:
Decision trees, support vector machines, and regression models are commonly used for predictive analytics in retail, focusing on stock management and demand forecasting.
Recommendation Systems:
Collaborative and content-based filtering are effective techniques for recommending products based on customer purchase patterns and product attributes.

Methodology:
Phase 1: Initial Assumption and Barcode Exploration
Assumption and Objective:
I began with the assumption that expiry date information would be encoded in the product barcode itself. Barcodes, which are typically used in retail stores for tracking product information, seemed like a promising data source. By scanning the barcode, I believed I could directly retrieve the expiry date and use it to trigger alerts for expiring products.

Technologies Used:
Pyzbar: A Python library designed to decode barcode data from images. It supports different types of barcodes, including EAN-13, UPC, and QR codes.
OpenCV: A widely-used computer vision library that helps with image processing, such as reading and decoding barcodes from images.
Pillow: A Python Imaging Library used to open, manipulate, and save images in different formats.
NumPy: Used for array operations in image manipulation, helping in efficient image processing with OpenCV.

Experimentation:
I started by experimenting with a sample product (e.g., Lay's packet) and used Pyzbar and OpenCV to decode the barcode. The barcode successfully revealed a product ID (EAN13 code), which is a unique identifier for the product. However, upon inspecting the decoded

data more closely, I realized that the expiry date was not present within the barcode's data fields. I examined several other products, including items like food and beverages, and found the same pattern—expiry date information was not stored in barcodes.

Challenges:

Despite using various techniques, including adjusting image quality and preprocessing with OpenCV, I could not extract expiry date information from the barcodes. The challenge was that barcodes in retail products generally contain only the product identifier and other logistical details (e.g., price, weight, or manufacturer), but not the expiry date.

Furthermore, I encountered technical issues with setting up the environment for barcode scanning. Specifically, I faced installation issues related to the library libzbar when working in Jupyter Notebook, which hindered the barcode scanning process. The solution required me to switch to Google Colab, where the libraries were pre-installed and ready to use.

Phase 2: Shifting to QR Code Exploration

Assumption and Objective:

Since QR codes have much larger storage capacities than traditional barcodes, I hypothesized that expiry date information might be embedded within QR codes instead. I turned my focus to extracting expiry date information from QR codes, which are increasingly used in retail for marketing and inventory management.

Experimentation:

I continued using Pyzbar, but this time for decoding QR codes. I uploaded images of products with QR codes and decoded them using the same process. However, I found that the QR codes mostly contained advertising and promotional URLs, rather than expiry date information.

I then attempted a live camera feed of QR code scanning to simulate real-time product checks in a store. However, the process was slow and inefficient. Scanning each product individually and using OCR would have been impractical for large-scale, everyday use in a busy retail environment.

Challenges:

The QR codes did not contain expiry date information as expected. This led me to reconsider QR codes as a reliable data source for expiry dates.

Real-time scanning of QR codes was slow, and it was not feasible to continuously monitor all products in the store using live feeds.

Phase 3: Leveraging Pytesseract OCR for Expiry Date Extraction

Assumption and Objective:

With neither barcodes nor QR codes providing the required expiry date information, I explored Optical Character Recognition (OCR) as a potential solution. OCR allows for the extraction of text from images, and I hypothesized that expiry date information might be printed on product labels or packaging.

Technologies Used:

Pytesseract: An open-source OCR tool that extracts text from images. It can recognize text in different fonts and sizes, making it suitable for identifying expiry dates printed on product labels.

OpenCV: Used for image preprocessing, such as resizing, binarizing, and enhancing the clarity of the text to improve OCR accuracy.

Pillow: Used for image manipulation to enhance the quality of images before feeding them into Pytesseract.

Experimentation:

I started by capturing images of product labels (which often display expiry dates) and ran them through Pytesseract for text extraction. The OCR tool successfully extracted some text, including expiry dates, from the labels of several products. However, it did not always yield accurate results, particularly for products with complex or low-resolution labels.

I further enhanced the images using OpenCV to remove noise, sharpen text, and improve contrast, which improved the accuracy of OCR

in some cases. Despite this improvement, I still faced limitations, especially with products that had difficult-to-read fonts or background noise.

Challenges:

OCR was not entirely reliable. In some cases, the expiry date was misinterpreted, particularly when the font was blurry, or the label was poorly printed.

In a retail setting, taking photos of all product labels for OCR could be time-consuming and inefficient, particularly with a large inventory.

Phase 4: Building the Dataset and Manual Data Entry

Dataset Creation:

Given the limitations of barcode, QR code, and OCR-based methods, I decided to manually create a dataset. I sourced 50 different retail products, including items with varying shelf lives, and manually entered their expiry dates and quantities into a structured dataset. The dataset included the following attributes for each product:

File Name: The name of the image or product.
Path: The location of the image.
Label: The product category or identifier.
Product Name: The name of the product.
Prize: The price of the product.
Quantity: The number of items available in stock.
Expiry Date: The expiry date of the product.

I entered this data through a combination of manual entry and information obtained from product tags.

1. Barcode-Based Expiry Date Extraction (Primary Approach)

1. Loading the Dataset and Structuring the Images

First, I loaded the Retail Product Checkout (RPC) Dataset and organized the images of the products within the structured directories. I ensured that the data structure was consistent and ready for preprocessing. The dataset contained 50 images, each associated with a product, and I manually created labels such as product_name, prize, quantity, and expiry_date.

2**. Preprocessing the Images**

The goal was to perform preprocessing on the barcode images to enhance the decoding process. I employed several techniques for image preprocessing, including:

Normalization: To scale pixel values for consistent processing and to reduce any intensity variation caused by lighting conditions.

Data Augmentation: I applied various transformations such as random rotation, flipping, and zooming to artificially increase the size of the training dataset and prevent overfitting.

Grayscale Conversion: I converted the images to grayscale to remove the color information and simplify the process for barcode decoders, focusing on the intensity of the pixels.

Thresholding: To improve the contrast between the barcode and the background, I applied binary thresholding. This allowed the algorithm to easily distinguish between the dark bars and light spaces of the barcode.

Edge Detection: I utilized edge detection techniques like the Canny Edge Detector to highlight the boundaries of the barcode, ensuring that the key features of the barcode were captured for decoding.

Image Resizing: I resized the images to a consistent size for efficient processing and to match the expected input size for the barcode reader.

Noise Reduction (Filtering): I used filtering techniques like Gaussian blur to reduce noise that might interfere with the clarity of the barcode. This helped improve the overall image quality before feeding it into the decoding algorithm.

After applying these preprocessing steps, I observed that the images became blurry and the colors changed, which negatively impacted the decoding process. The preprocessing caused the barcodes to be distorted, and I could not successfully decode the information. This led to the decision to restart the preprocessing pipeline.

3. Revised Approach - No Preprocessing

Upon re-evaluation, I decided to bypass the preprocessing steps entirely and directly decode the images from the dataset. This new approach proved more effective, as I was able to retrieve accurate barcode information without any distortions.
After decoding all 50 images, I successfully extracted the following information:
Decoded information from the image img45.jpg:
Type: CODE128
Data: 00010700519528
Product Name: RANCHER CHEWS
Brand: Hershey's
Description: INGREDIENTS: SUGAR; CORN SYRUP; PALM OIL; CONTAINS 2% OR LESS OF: MALIC ACID; GELATIN; NATURAL AND ARTIFICIAL FLAVOR; GLYCERYL MONOSTEARATE; ARTIFICIAL COLOR (RED 40; YELLOW 5; BLUE 1; YELLOW 6); SULFUR DIOXIDE, TO MAINTAIN FRESHNESS; CORNSTARCH; SOY LECITHIN.
Image URL: http://www.meijer.com/assets/product_images/styles/xlarge/1001029_010700519528_A_400.jpg
The first approach focuses on leveraging barcode data to automatically extract expiry date information from product barcodes. The vision here is to make the process as streamlined as possible, where the entire workflow consists of only two simple steps:
Scan the Product: The barcode on each product is scanned using a barcode scanner or camera.
Decode the Expiry Date: If the expiry date information is embedded in the barcode, it is automatically decoded using a barcode reader or a specialized decoding algorithm.
This two-step process allows for a highly efficient system that does not require manual intervention, saving time for store staff and ensuring accurate, real-time expiry tracking.
Here's how this works:
Barcode Embedding of Expiry Dates: Many products contain expiry date information embedded within the barcode, typically in the form of a code like CODE128. This code can store product information, including the expiry date, in a structured format.
Automated Pop-Up Alerts: Once the barcode is scanned and decoded, the expiry date can be extracted. The system will then trigger a pop-up notification when the product is nearing its expiry date, providing an alert to staff that action needs to be taken—either by placing the product in clearance or pulling it off the shelves.
Benefits of this approach:
Automation: This approach reduces manual work, as the expiry information is directly retrieved from the barcode, and no additional manual input is required.
Speed and Efficiency: The two-step process of scanning and decoding allows for quick real-time expiry management, ensuring that expired products are not missed.
Accuracy: The barcode-based system is highly accurate since the expiry date information is coded directly into the product's barcode, reducing the risk of human error.

Challenges Faced with Barcode Decoding
While this method is ideal, there are some limitations that you encountered during your project:
Not All Barcodes Contain Expiry Information: Some products may not have expiry dates encoded in their barcodes. In such cases, the decoding algorithm would fail to provide the necessary information, which can lead to a gap in tracking expiry dates.
Image Preprocessing Issues: During the image preprocessing steps (like normalization and thresholding), you noticed that the images became blurry, and the colors were altered. This affected the clarity of the barcodes and made it difficult to decode the data. This is a crucial challenge because barcode decoders require high-quality, sharp images for accurate reading.
Despite these challenges, you aimed to retry the barcode-based approach without preprocessing steps, achieving the goal of extracting expiry dates from the product barcodes. This is the core

automation method for your project, providing a streamlined solution if expiry dates are available in the barcodes.

Manual Expiry Date Entry (Backup Approach)

Because not all products may have expiry dates embedded in their barcodes, introduced a second method to handle these cases—manual expiry date entry. This approach involves human intervention during the inventory cycle count:

Employee Responsibility: During the regular cycle count process, store employees manually enter the expiry date information for products that do not have this data in the barcode.

Data Entry Workflow: The employee enters the expiry date information in the store's system (or database), ensuring that all products are tracked even if the barcode doesn't contain expiry data.

	file_name	path	label	product_name	prize	quantity	expiry_date
0	img1.jpg	expiry_barcode_dataset/images/train\img1.jpg	train	lays_sourcreamandonion	4.99	10	2/19/2025
1	img10.jpg	expiry_barcode_dataset/images/train\img10.jpg	train	funguns	5.49	6	6/24/2025
2	img11.jpg	expiry_barcode_dataset/images/train\img11.jpg	train	7SHotMangoHoneyBun	1.99	5	5/3/2025
3	img12.jpg	expiry_barcode_dataset/images/train\img12.jpg	train	7SBreadSlicecklcedLmn	1.00	8	6/14/2025
4	img13.jpg	expiry_barcode_dataset/images/train\img13.jpg	train	7SMuffinBananaWalnut	2.89	9	12/24/2025
5	img14.jpg	expiry_barcode_dataset/images/train\img14.jpg	train	BnAPMuffinBlueberry	2.99	15	11/24/2025
6	img15.jpg	expiry_barcode_dataset/images/train\img15.jpg	train	cinnamon_roll	3.29	6	12/28/2024
7	img16.jpg	expiry_barcode_dataset/images/train\img16.jpg	train	bnApPanDeQueSoCheeseCake	2.99	10	5/12/2025

After structuring the data, I proceeded with the following data preprocessing steps:

Exploratory Data Analysis (EDA):

I performed an EDA to understand the distribution of product prices, quantities, and expiry dates. Visualizing the data helped identify any potential patterns or outliers that could affect the analysis and predictions.

Handling Missing Data:

I checked for missing values in the dataset and handled them appropriately. For numerical data (like price and quantity), I filled missing values with the mean or median. For categorical data (like product names), I used a mode imputation method or dropped the rows if they were crucial.

Feature Engineering:

Extract Features from Expiry Date: I extracted the year, month, and day from the expiry date column to help in the prediction model. This can assist in analyzing the time-related patterns for product expiry.

Categorical Encoding:

I encoded categorical columns like product_name and brand using techniques like Label Encoding or One-Hot Encoding to make the data machine-readable.

Correlation Matrix:

I calculated the correlation between numerical columns like price, quantity, and expiry-related features to understand how they interact with each other.

Time-Based Analysis:

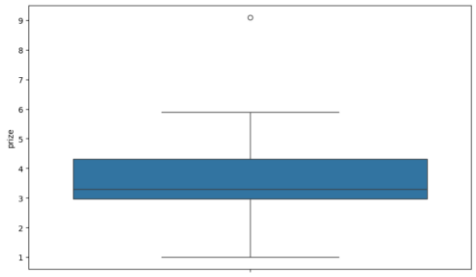
I focused on products expiring within the next 30 days. This was important for identifying products that need to be cleared out to avoid wastage.

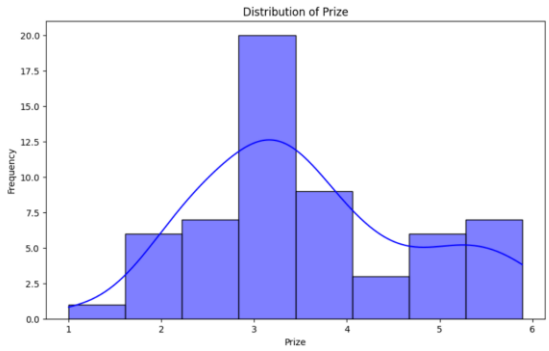
Visualization:

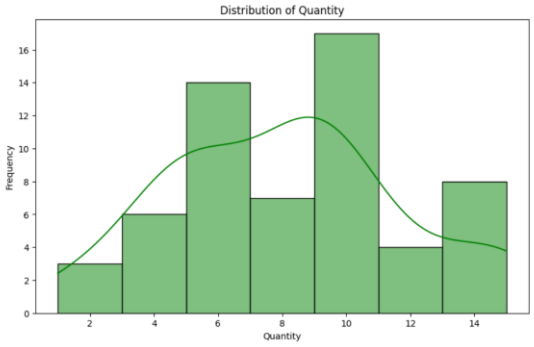
I visualized the relationship between numerical columns using pairplots to see how price, quantity, and expiry-related features correlate with each other.

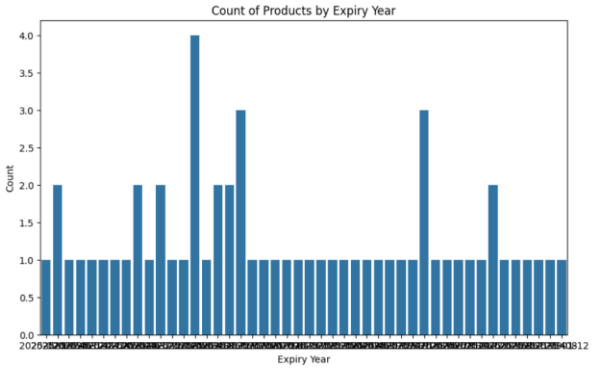
Products Expiring in the Next 30 Days:

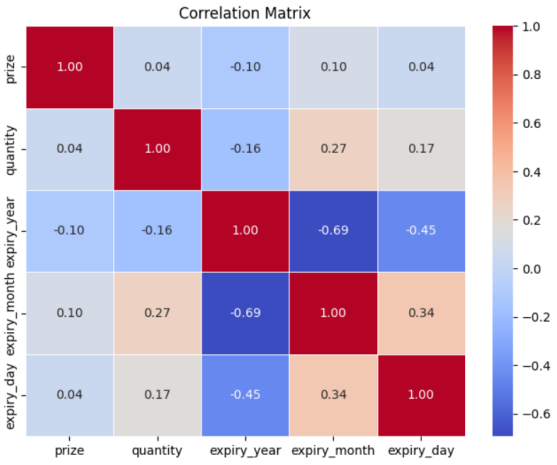
I visualized the products expiring soon to help with decision-making for clearance sales.

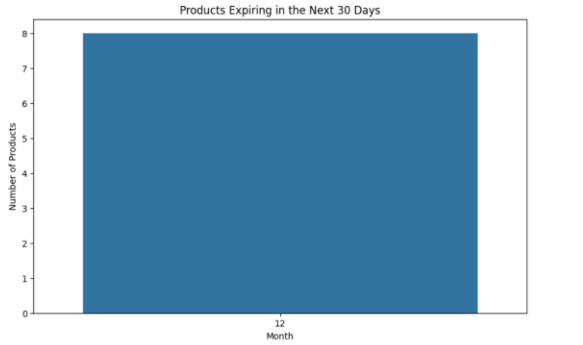


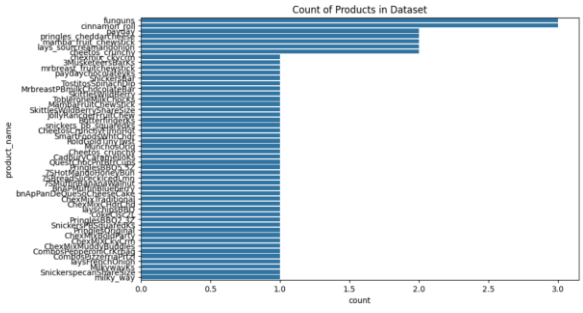








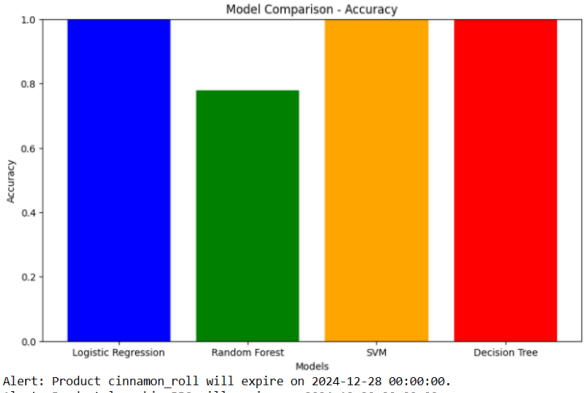




Modeling:

After building the dataset, I turned my attention to predicting expiry dates and recommending products for clearance sales. I applied various machine learning models, starting with classification models like Decision Trees, SVM, and Random Forest to predict whether a product would expire within a certain time frame.

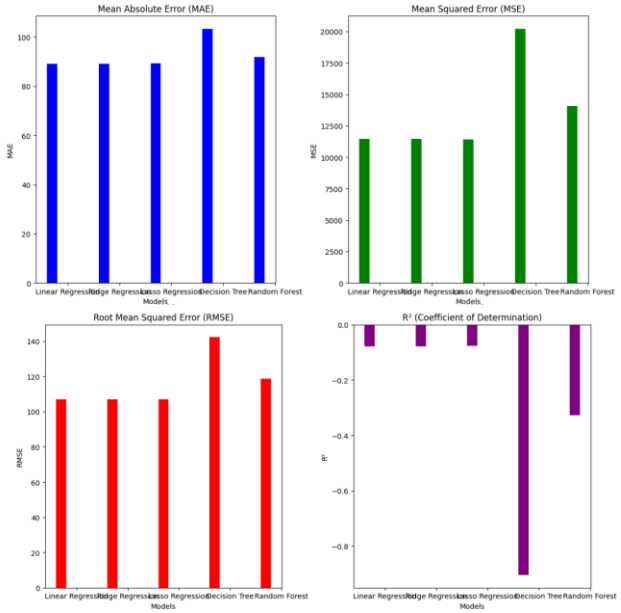
Classification Models: I used decision trees, which performed well in predicting when products were nearing their expiry dates, based on their features like price, quantity, and product type.




```
Alert: Product cinnamon_roll will expire on 2024-12-28 00:00:00.
Alert: Product layschipsBBQ will expire on 2024-12-20 00:00:00.
Alert: Product Cheetos_crunchy will expire on 2024-12-20 00:00:00.
Alert: Product CheetosCrunchyFlmnHot will expire on 2024-12-31 00:00:00.
Alert: Product mamba_fruit_chewstick will expire on 2024-12-31 00:00:00.
Alert: Product pringles_cheddarcheese will expire on 2024-12-25 00:00:00.
Alert: Product payday will expire on 2024-12-25 00:00:00.
Alert: Product mamba_fruit_chewstick will expire on 2024-12-31 00:00:00.
```

```
ALERT: The product 'layschipsBBQ' (SKU: img2.jpg) is expiring on 12/20/2024. Please take necessary actions.
ALERT: The product 'Cheetos_crunchy' (SKU: img5.jpg) is expiring on 12/20/2024. Please take necessary actions.
ALERT: The product 'CheetosCrunchyFlmnHot' (SKU: img6.jpg) is expiring on 12/31/2024. Please take necessary actions.
ALERT: The product 'payday' (SKU: img8.jpg) is expiring on 12/25/2024. Please take necessary actions.
```

Regression Models: I also applied regression models such as Linear Regression, Lasso, and Ridge to predict the exact number of days left before a product's expiry.



Among the models, Decision Trees yielded the best performance, capturing the underlying patterns in the data, while regression models provided more granular predictions.

```
Products that will expire within 30 days:
  product_name         predicted_expiry_date
0         Milk 2024-04-21 23:02:24.000000000
1       Cheese 2024-05-23 16:45:25.714285715
2       Yogurt 2024-04-30 04:23:59.999999997
```

	product_name	expiry_date
0	lays_sourcreamandonion	2025-02-19
1	funguns	2025-06-24
2	7SHotMangoHoneyBun	2025-05-03
3	7SBreadSliceckIcedLmn	2025-06-14
4	7SMuffinBananaWalnut	2025-12-24
5	BnAPMuffinBlueberry	2025-11-24
6	cinnamon_roll	2024-12-28
7	bnApPanDeQueSoCheeseCake	2025-05-12

Phase 5: Incorporating Recommendation Techniques

Objective:

To further enhance the solution, I incorporated recommendation systems to help store managers identify products that should be cleared before they expire. The goal was to suggest products for early clearance or sale, ideally before they reached their expiry date.

Recommendation Techniques:

Collaborative Filtering: I explored user-item collaborative filtering methods, which recommend products based on customer preferences. I assumed that products with similar expiry timelines or high purchase frequencies could be recommended for clearance.

```
Near Expiry Products:
             product_name expiry_date  days_until_expiry
6           cinnamon_roll  2024-12-28                 23
11           layschipsBBQ  2024-12-20                 15
40        Cheetos_crunchy  2024-12-20                 15
41   CheetosCrunchyFlmnHot  2024-12-31                 26
46   mamba_fruit_chewstick  2024-12-31                 26
50  pringles_cheddarcheese  2024-12-25                 20
53                 payday  2024-12-25                 20
58   mamba_fruit_chewstick  2024-12-31                 26
Frequent Product Pairings:
Pair: ('lays_sourcreamandonion', 'lays_sourcreamandonion'), Count: 25
Pair: ('payday', 'payday'), Count: 23
Pair: ('funguns', 'funguns'), Count: 22
Pair: ('mamba_fruit_chewstick', 'mamba_fruit_chewstick'), Count: 18
Pair: ('BnAPMuffinBlueberry', 'BnAPMuffinBlueberry'), Count: 15

Recommended Near Expiry Products Bought Together:
Product Pair: payday & payday
Product Pair: mamba_fruit_chewstick & mamba_fruit_chewstick
```

Content-Based Filtering: I used product features such as expiry date, price, and quantity to recommend items similar to those with upcoming expiry dates. For example, products nearing their expiry could be offered to customers who previously bought similar items.

Matrix Factorization: By applying matrix factorization techniques, I identified latent features that correlated with products nearing expiry and created a system to recommend products based on these hidden factors.

```
Recommended products for clearance:
             product_name expiry_date  days_until_expiry
11           layschipsBBQ  2024-12-20                 15
40        Cheetos_crunchy  2024-12-20                 15
50  pringles_cheddarcheese  2024-12-25                 20
53                 payday  2024-12-25                 20
6           cinnamon_roll  2024-12-28                 23
41   CheetosCrunchyFlmnHot  2024-12-31                 26
46   mamba_fruit_chewstick  2024-12-31                 26
58   mamba_fruit_chewstick  2024-12-31                 26
```

Analysis:

The project adopted a phased approach:

Phase 1: Barcode decoding revealed product identifiers but not expiry dates.

Phase 2: QR code decoding contained promotional data but no expiry information.

Phase 3: OCR successfully extracted expiry dates from product labels but faced limitations with low-resolution images.

Phase 4: A structured dataset of 50 products was manually created, including attributes such as product name, price, quantity, and expiry date.

Phase 5: Machine learning models were employed to predict expiry dates, and recommendation techniques facilitated clearance sales.

Limitations:

1. Barcodes and QR codes generally lack expiry date information.
2. OCR accuracy is limited by image quality and text noise.
3. Real-time scanning of all products is impractical for large inventories.
4. Manual data entry is labor-intensive and prone to human error.

Results:

1. OCR achieved moderate success in extracting expiry dates from labels.
2. Decision Tree models provided accurate predictions for products nearing expiry, with the highest performance among tested algorithms.
3. Recommendation systems effectively identified products suitable for clearance sales.

Conclusion/Discussion:

The project demonstrated that automated expiry date management is feasible with a combination of barcode decoding, OCR, and machine learning. However, the absence of expiry data in barcodes and QR codes remains a significant limitation. The integration of manual data entry and structured datasets proved crucial for effective tracking. Machine learning models and recommendation systems enhance decision-making for inventory management.

Future Work:

- Explore the potential of integrating expiry dates into barcodes or QR codes.
- Develop advanced OCR preprocessing techniques to improve accuracy.
- Scale the system for real-time deployment in large retail stores.
- Incorporate customer feedback into recommendation systems for personalized suggestions.
- Investigate deep learning models for more accurate expiry prediction and text extraction.

Sources:

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Pyzbar: Pyzbar Documentation
OpenCV: OpenCV Documentation
TensorFlow: TensorFlow Documentation
PIL (Python Imaging Library): Pillow Documentation
Scikit-Image: Scikit-Image Documentation

"Turning the ticking clock of expiry into an opportunity for smarter inventory, reduced waste, and fresher products—where AI meets sustainability and efficiency."