Smart Supermarket System

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***Abstract*—In this paper, we tackle the challenge of product recommendation in a supermarket setting. We introduce a hybrid recommender system that integrates Collaborative Filtering and Content-Based Filtering, enhancing recommendation accuracy and relevance by considering both historical data and current customer states. Key features of our system include face recognition for identity verification, emotion detection for mood-based product suggestions, and dynamic pricing strategies to encourage the sale of products nearing expiration. Validated through simulations and real-world datasets, including the publicly available Instacart dataset, this study advances customer behaviour analysis and sustainable marketing by offering a more dynamic and personalized shopping experience while promoting waste reduction.**

***Index Terms*—Hybrid Recommender System, Collaborative Filtering, Content-Based Filtering, Computer Vision, Machine Learning**

I. Introduction

Technology has made online grocery shopping more accessible, however, in-store shopping continues to play a vital role in people's daily routines. Recent findings indicate that around 30% of Canadians purchase some groceries online, yet only 4% rely primarily or exclusively on online platforms for their grocery needs. In contrast, nearly 50% of consumers in the United States engage in online grocery shopping [1]. The average number of trips Canadians make to the grocery store per month has increased to 7.20, up from 5.43 in 2018 [2]. Meanwhile, Americans have maintained a steady average of approximately 6.40 trips per month since 2013 [3].

The sustained demand for in-store shopping highlights the potential for supermarkets to enhance their services by enriching customers' shopping experiences through recommendation systems. Such systems can provide personalized product suggestions based on individual preferences. Developing effective recommendation systems can be a key factor in elevating the shopping experience and, ultimately, driving sales growth.

Traditional recommendation systems often rely heavily on customers' past purchase histories [4], [5], leading to less personalized suggestions. However, purchasing decisions are complex and can be influenced not only by shopping habits but also by other factors, such as the emotions a customer experienced at the time of purchase [6]. Additionally, manually identifying individual preferences is challenging, as these preferences can change unpredictably [7], and this task becomes nearly impossible when dealing with a vast array of available products. These challenges underscore the need for a more comprehensive and adaptive recommendation system capable of managing large amounts of data and accommodating the dynamic nature of customer behaviour.

To address these challenges, our objective is to develop a supermarket recommendation system that integrates face recognition, emotion detection, customer purchase history, and expiring food inventory data. This multi-faceted system aims to provide more personalized product recommendations, encourage purchases, and reduce food waste.

This paper is structured as follows: Section II Related Work provides a summary of existing relevant studies in the fields of Face Recognition and Emotion Detection, Personalized Recommendation Systems, and Dynamic Pricing. Section III Problem Statement defines the problem and establishes the metrics for performance evaluation. Section IV Algorithms outlines the workflow of our program and elaborates on the models and techniques utilized in developing our recommendation system. Section V Simulation Design details the steps for setting up scenarios, handling data, and analyzing the outcomes. Section VI Results presents the outcomes of our work, including model performance scores and an analysis of user survey results. Section VII Limitation and Future Work discusses the limitations encountered in our project and suggests potential improvements for future research. Finally, Section VIII Conclusion summarizes the goals and objectives we have achieved.

II. Related work

A. Face Recognition and Emotion Detection

Face recognition is a technology that offers non-contact and convenient identification. There are several existing models widely used across various fields. For example, Schroff et al. [8] introduced FaceNet, a deep learning face recognition method that achieved a record-breaking accuracy of 99.63% on the Labeled Faces in the Wild (LFW) dataset by directly optimizing the embedding rather than using an intermediate bottleneck layer. The evolution of deep learning architectures, from OpenCV and AlexNet to more advanced models like VGGNet, ResNet, and SENet, has also significantly improved the ability to extract robust features for face recognition [9]–[11].

Emotion detection is closely related to face recognition. Hussain et al. [12] present a real-time face emotion classification and recognition system employing deep learning algorithms. This system utilizes phases such as face detection, face recognition, and face classification to categorize emotions like happiness, anger, sadness, and surprise. Similarly, Yang et al. [13] propose a real-time facial expression recognition algorithm based on edge computing, analyzing micro-expressions through facial muscles and mapping them to eight distinct facial expressions.

B. Recommendation Systems

Personalized recommendation systems aim to predict items of interest for individual users and have been extensively studied over the past decade. In 2011, Pradel et al. [4] conducted a systematic comparison of various collaborative filtering systems using a real-life purchase dataset. They demonstrated that recommender systems could be effectively developed based on purchase data rather than rating data, highlighting the differences in algorithm performance between these contexts. In 2018, Wan et al. [14] utilized product complementarity, preference compatibility, and user loyalty to inform product recommendations related to repeated consumption behaviour. The study outlined in [15] introduces a recommendation system tailored for virtual shopping environments like SmartMart. This system integrates collaborative filtering algorithms to analyze purchase histories and customer preferences, generating item-based, user-based, and popularity-based recommendations. Similarly, Yi and Liu [16] delve into machine learning-based customer sentiment analysis to improve product recommendations based on customer reviews. By analyzing feedback related to manufacturing date, price, and product quality, their system employs collaborative filtering and product-product similarity to refine its recommendations. In 2021, Shamika and De Silva [5] developed a recommendation model based on the shopping history of consumers using Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and collaborative filtering. They concluded that collaborative filtering was the most effective technique for their model.

C. Relationship between Emotions and Food Choices

Food impacts mood, while mood guides food choice. Macht's five-way model on emotion-induced changes in eating suggests that emotional eaters consume more food to mitigate negative emotions, while restrained eaters on a diet increase their food intake in response to both positive and negative emotions [17]. AlAmmar et al. [18] highlight that appropriate food choices play a significant role in mood enhancement. Evers et al. [19] note that positive emotions can encourage eating, while negative emotions lead to increased food intake in restrained eaters. King and Meiselman [20] classify various consumer emotions into three categories: positive, negative, and unclear. They observe that most food-related experiences are perceived positively by healthy individuals and emphasize that a consumer's acceptance of a product is closely linked to their emotional profile.

D. Dynamic Pricing

Dynamic pricing is a strategy where prices are adjusted in real time based on demand and other market factors to maximize revenue and efficiency. Several papers [21]–[23] present models that offer discounts based on expiration dates, aiming to increase sales likelihood and reduce waste. Bauer and Jannach [24] provide a framework for dynamic pricing in e-commerce, utilizing Bayesian inference and kernel regression to handle sparse and noisy data for real-time price adjustments.

Some studies also consider inventory monitoring and carrying costs when determining optimal pricing to maximize profits. Liu et al. [25] note that these costs significantly impact the optimal price, and in some cases, the optimal price may not always decrease. Yang et al. [26] evaluate a quality-based pricing strategy using a deep reinforcement learning algorithm in grocery retailing. Their simulations show that combining information disclosure with dynamic pricing leads to higher profits and reduced food waste.

E. Research Gap

Previous research on supermarket product recommenders has predominantly focused on providing recommendations based on users' past purchases or the approaching expiration of products. Little attention has been given to how customers' moods during shopping might influence their purchasing decisions or how these factors combined might jointly affect their choices.

In this paper, we explore a comprehensive recommendation system that leverages various data sources, including face identification, emotion detection, past customer purchases, and expiring food inventory. Our approach uniquely combines these factors to enhance personalized recommendations by considering both past purchase habits and customers' current moods, while also minimizing food waste. This integration provides a more effective solution in a supermarket setting.

III. Problem Statement

Our research enhances the accuracy and relevance of supermarket recommendation systems by integrating multiple data sources, including customer emotions, purchase history, and product shelf life. We propose developing a recommendation algorithm that dynamically adjusts recommendations based on detected user emotions and the varying shelf life status of products to ensure relevance.

The performance of our system is evaluated using the following metrics:

1) Face Recognition and Emotion Detection Accuracy: The program should be capable of correctly identifying customers and detecting their current emotions. The accuracy of face identification and emotion detection is evaluated by the detection success rate, using the faces and emotions of our team members as benchmarks.

2) Recommendation Alignment: The product recommendations provided by the system should align with the intake information, incorporating factors such as current mood, previous purchases, and expiring products. We get initial recommendations based on purchase history. From these initial recommendations, we derive current emotion-related products and close-to-expiration products. The effectiveness of how well the recommendations we get from our models is measured using precision, recall, and F1 score.

Precision measures the accuracy of the recommendation system in terms of how many of the recommended items were actually useful to the users. A higher precision value indicates that a greater proportion of the recommended items were relevant and bought by the users.

Recall measures the ability of the recommendation system to identify all relevant bought items. A higher recall indicates that the model was able to recommend a larger proportion of the items that were actually bought.

The F1 score provides a combined measure of precision and recall, taking both into account to give a single score that reflects the overall effectiveness of the recommendation system. A higher F1 score indicates that the system has a good balance between precision and recall, meaning it not only makes accurate recommendations but also covers most of the relevant items.

The formulas of performance metric of obtaining initial recommendations are shown below:

$$\text{Precision} = \frac{|\text{Recommended Items from Model} \cap \text{Actual Bought Items from Test Set}|}{|\text{Recommended Items from Model}|} \tag{1}$$

$$\text{Recall} = \frac{|\text{Recommended Items from Model} \cap \text{Actual Bought Items from Test Set}|}{|\text{Actual Bought Items from Test Set}|} \tag{2}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

The formulas of performance metric of obtaining current emotion-related products and close-to-expiration products are shown below:

$$\text{Precision@N} = \frac{\text{Number of Top-N Similar items from Same Aisle as the Given item}}{\text{N}} \tag{4}$$

$$\text{Recall@N} = \frac{\text{Number of Top-N Similar items from Same Aisle as the Given item}}{\text{Total Number of items from Same Aisle as the Given item}} \tag{5}$$

$$\text{F1@N} = 2 \times \frac{\text{Precision@N} \times \text{Recall@N}}{\text{Precision@N} + \text{Recall@N}} \tag{6}$$

3) Impact Assessment on Sales and Waste Reduction: Since the original dataset does not include product prices and there is no available public price dataset broad enough to cover the scope of our project, it is difficult to directly assess the recommendation system's impact on supermarket profits. Chun [27] noted that retailers frequently use Expiration Date-Based Pricing (EDBP) as an effective revenue management tool to boost purchases and minimize waste by lowering the prices of perishable goods as their expiration dates approach. Inspired by this, our primary goal is to encourage sales and minimize food waste by promoting close-to-expire products.

IV. Algorithms

A. Workflow

Figure 1 illustrates our supermarket recommendation system's workflow. Users, upon signing up or logging in, upload a photo which is used for face identification and mood detection. New users need to fill out a preference form for the system recommending products accurately. An initial recommendation list is generated by the Collaborative Filtering Model based on customers' past purchase history. Then, the system identifies the most similar products from the initial recommendations within the current emotion-related product list and close-to-expiration product list utilizing Content-based Filtering Model. Ultimately, the filtered products are presented to the user as the final recommendation.

B. Recommendation Process Using Pseudocode

```
# Step 1: User login
user = login()

# Step 2: Detect user emotion,
# get user current emotion
current_emotion = detect_user_emotion(user)

# Step 3: Get current emotion-related products
emotion_related_products = get_emotion_related_products(current_emotion)

# Step 4: Get initial recommendations
# from Collaborative Filtering Model (CFM)
initial_recommendations = get_initial_recommendations(user, CFM)

# Step 5: Define method to get product neighbors
# using product embeddings from Content-Based Filtering (CBF) model
def get_product_neighbors(product, product_embeddings):
    neighbors = []
    for other_product in product_embeddings:
        similarity = calculate_similarity(product, other_product)
        if similarity <= 0.0001:
            neighbors.append(other_product)
    return neighbors

# Step 6: For each item in initial recommendations,
# find the most similar products in current emotion-related product list
emotion_related_recommendations = []
for item in initial_recommendations:
    similar_products = get_product_neighbors(item, emotion_related_products)
    emotion_related_recommendations.extend(similar_products)

# Step 8: Return top 5 initial recommendations,
# top 3 current emotion-related recommendations,
# top 3 close-to-expiration recommendations
top_initial_recommendations = initial_recommendations[:5]
top_emotion_related_recommendations = emotion_related_recommendations[:3]
top_close_to_expiration_recommendations = close_to_expiration_recommendations[:3]
```

Fig. 2: Pseudocode of the Recommendation Process

C. Collaborative Filtering Model

Collaborative filtering(CF) is a technique the system uses to automatically predict a user's interest by collecting other users' preferences or taste information and then automatically

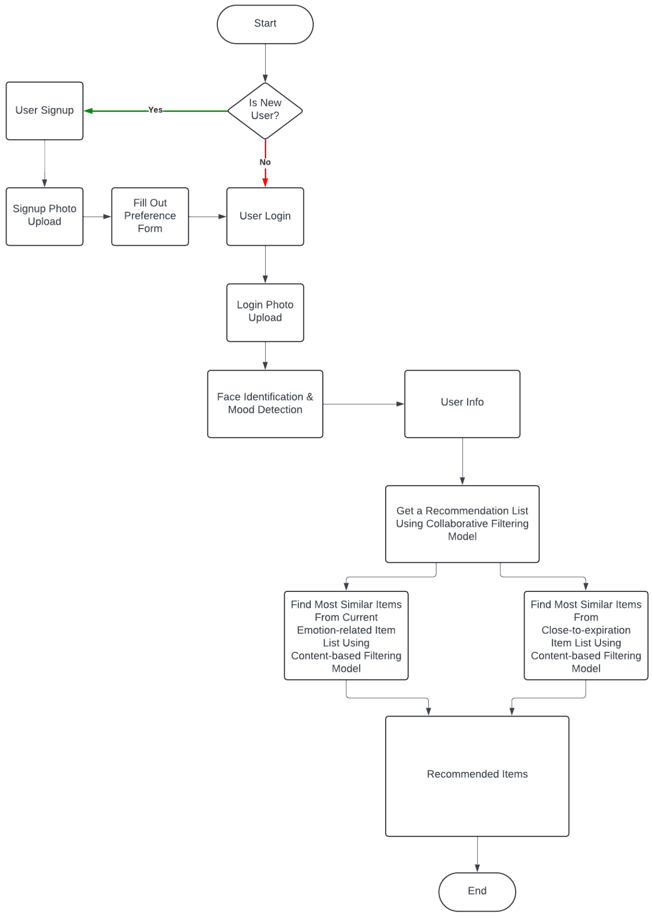


Fig. 1: Proposed Workflow for Supermarket Recommendation System

combining them to make a prediction. CF relies on the assumption that, if person A has the same opinion as person B on an issue, they are more likely to have a person B's opinion on some other issue than that of a randomly picked individual.

1) Matrix Factorization: One of the most common approaches for collaborative filtering is matrix factorization. Initially, we experimented with Singular Value Decomposition (SVD) and compared its performance with Alternating Least Squares (ALS).

a) Singular Value Decomposition (SVD): SVD is a technique that decomposes a matrix into three other matrices, capturing latent factors representing user preferences and item characteristics. However, SVD can sometimes be less effective for large and sparse matrices typical in collaborative filtering scenarios.

b) Alternating Least Squares (ALS): ALS, on the other hand, iteratively optimizes user and item embeddings by alternating between fixing one and solving for the other. This method tends to perform better with sparse data and scales well to large datasets.

Based on our comparisons, we ultimately chose ALS due to its superior performance. Our custom matrix factorization method involves decomposing the user-item interaction matrix into two lower-dimensional matrices: user embeddings and product embeddings. These embeddings capture latent factors representing the user's preferences and the product's characteristics. We initialize the user and product embeddings with random values. The hyperparameter "embedding dimension" determines the dimensions of these embeddings.

D. Content-based Filtering Model

Content-Based Filtering (CBF) is a recommendation technique that utilizes features of products and users to generate recommendations. Unlike Collaborative Filtering (CF), which relies on user-item interactions, CBF focuses on analyzing item attributes and user preferences to make personalized recommendations. In our project, we do not use CBF to make recommendations directly; instead, we use product embeddings generated by the CBF model to calculate product similarities.

While it is possible to use product embeddings from CF models to calculate product similarities, we opted to use the product embeddings from the CBF model instead. This choice is motivated by the fact that the CBF model leverages actual product information, such as product aisles and departments, to generate embeddings. These embeddings are directly informed by the products' real-world characteristics, resulting in more accurate and relevant product similarities. Our results indicate that the CBF model outperformed the ALS model in generating more accurate and relevant product similarities.For detailed results, please refer to Section VI Results.

The similarity between two products can be calculated using the squared Euclidean distance, defined as follows:

$$\text{Distance}(\mathbf{p}_i, \mathbf{p}_j) = \sum_{k=1}^{n} (\mathbf{p}_{i,k} - \mathbf{p}_{j,k})^2$$

where:

- $\mathbf{p}_i$ and $\mathbf{p}_j$ are the embedding vectors of products i and j,
- $\mathbf{p}_{i,k}$ and $\mathbf{p}_{j,k}$ are the k-th components of the embedding vectors,
- n is the dimensionality of the embedding vectors.

To implement our content-based filtering model, we followed a structured approach:

1) User Feature Engineering: We calculated the purchase count for each aisle and department that a user has interacted with. This process aggregates data to construct a detailed profile for each user, capturing their shopping habits and preferences.

2) Product Feature Engineering: For products, we derived features that include average purchase counts and binary indicators representing associations with different aisles and departments. A binary value of 1 indicates the product's presence in a specific aisle or department, while 0 signifies absence. This approach effectively encodes categorical data, enhancing the generation of distinct product profiles based on observed purchase patterns.

3) Implementation Using Neural Networks: Our content-based filtering model employs a neural network architecture. This neural network is designed to learn and optimize user preferences and product features derived from the feature engineering process.

This structured implementation of the content-based filtering model allowed us to leverage detailed product information and user preferences, resulting in a robust recommendation system that outperformed the collaborative filtering model in finding product neighbors.

E. Hybrid Recommendation Model

Our project provides a hybrid recommender system that integrates Collaborative Filtering and Content-Based Filtering to leverage the strengths of both approaches for improved recommendation accuracy and relevance.

Collaborative Filtering analyzes historical user-item interactions to provide initial product suggestions. It identifies products that similar users have interacted with, based on past purchase behaviour. This approach is effective in suggesting popular items or those preferred by users with similar tastes.

Content-Based Filtering refines initial recommendations by considering contextual factors such as user emotions and product shelf life. It identifies the most similar products from the initial CF recommendations within the current emotion-related product list and close-to-expiration product list. By analyzing attributes like emotional relevance and shelf life proximity, it enhances recommendation relevance based on user-specific contexts.

F. Face Recognition and Emotion Classification

DeepFace is a Python-based facial analysis framework that performs both face recognition and demographic analysis. It enables rapid identification of target images within seconds by storing vector representations of faces in a pickle file upon the initial execution of the find function, thus facilitating face recognition on large datasets [28]. Cosine Similarity is the default configuration for face verification. The VGG-Face model has been chosen as the default for this project due to its consistently high performance in face recognition tasks [29].

Emotion detection is part of DeepFace's facial attribute analysis component, which can identify seven facial expressions: anger, fear, neutrality, sadness, disgust, happiness, and surprise. The detected emotion is passed into the mood-food mapping system to identify suitable supermarket food items for the customer.

G. Mood-food Mapping

The food-mood mapping follows a two-step process. First, emotions detected by DeepFace are categorized into three groups—positive, negative, and unclassified—following King and Meiselman's classifications. Next, drawing on [17], [20], [30] on the impact of emotions on eating behaviours—indicating that negative emotions often lead to increased indulgence in food high in sugar, salt, and fat, while positive emotions promote consumption or nutrient-rich healthy foods— these findings are applied to categorize supermarket products, which reorganized by aisle_id. These mood-based groupings are then cross-referenced with the recommendations generated by the recommender system.

H. Expiration Dates Ranking and Dynamic Pricing

To simplify the complex dynamic pricing strategies explored in previous research, we focus solely on determining whether to apply a discount based on the expiration date, without considering the discount rate. In our recommendation system, products are ranked according to their expiration dates, prioritizing items that are closest to expiration. Tsiros and Heilman (2005) found that consumers' willingness to purchase discounted perishable goods increases as the expiration date approaches, particularly within the last few days before expiration [31]. Therefore, for products in expiring within 30 days are eligible for discounts based on the number of days until their expiration. This approach aligns with research by den Boer et al. (2022), which shows that markdown pricing policies, offering discounts on expiring products, can effectively reduce waste and increase profits by enhancing customers' willingness to buy items nearing their expiration dates [32]. Their study demonstrates that a simple markdown scheme can be advantageous for both profit enhancement and waste reduction.

V. Simulation Design

A. Program Environment

Our system is implemented using Python 3.8 and Flask 2.0.1 for the backend server. We chose Python for its rich ecosystem of machine learning libraries and Flask for its lightweight nature and ease of integration with various components. The frontend is developed using React 17.0.2, providing a responsive and interactive user interface. Our frontend is also connected to a Firebase database, which is used to store user information.

For face recognition and emotion detection, we utilize the DeepFace library 0.0.75. The recommendation system is built using scikit-learn 0.24.2 for collaborative filtering and TensorFlow 2.5.0 for neural network-based content filtering.

This environment was selected for its balance of performance, ease of use, and compatibility with our chosen algorithms and libraries.

B. Dataset

Figure 3 shows the original dataset schema of "Instacart Market Basket Analysis" [33] used for our project. It is a relational set of files detailing customers' grocery orders over time. It includes a sample of over 3 million grocery orders from more than 200,000 Instacart users. Each user has between 4 and 100 orders recorded, with details of the products purchased in each order.

The original dataset includes two key files: `order_products__prior.csv` and `order_products__train.csv`. The former contains previous order contents for all customers, while the latter contains the latest order contents for all customers. In our project, we use `order_products__prior.csv` to train the model and use `order_products__train.csv` to test the model.

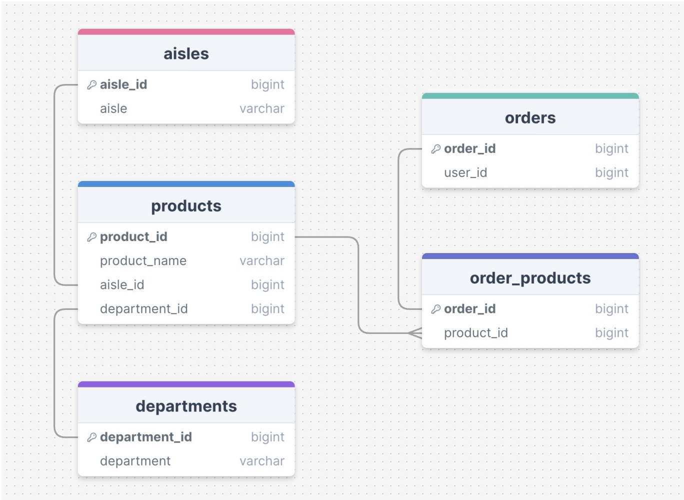


Fig. 3: Original Dataset Schema

No.	Field	Description
1	product_id	Id of product
2	product_name	Name of product
3	user_id	Id of user
4	purchase_count	Number of times a product purchased by the user
5	aisle_id	Id of product aisle
6	aisle	Name of product aisle
7	department_id	Id of product department
8	department	Name of product department

TABLE I: Sample Dataset attributes. Here, 'aisle' does not refer to the physical location of products but rather the category of products.

Customer emotion data is obtained through our facial recognition system, which analyzes photos uploaded by users. Based on previous research on how mood affects eating and consumption behaviour, we mapped food items to emotions and categorized them by aisle_id. This mapping will be further used to determine which recommendations from our models are the best fit for the consumer.

Since the original dataset does not include product expiration dates and acquiring public data is challenging, we decided to set a certain proportion of near-expiration products in our dataset, referencing publicly available supermarket disposal rate data. Based on reference data [34] indicating that departments such as produce, bakery, and meat lose approximately 4.5% of their goods to spoilage, and 2% for other products, we will randomly assign expiration dates to these proportions of products (4.5% of produce, bakery, and meat seafood will expire in 3 days, and 2% of other products will expire in 30 days). This will allow us to filter out close-to-expire products effectively.

C. Computer Vision

Our program utilizes DeepFace to handle the computer vision component. DeepFace is renowned for its high accuracy in facial detection and robust performance across various datasets, aligning perfectly with our requirement for face identification across diverse consumer groups. DeepFace not only analyzes facial attributes, including emotion detection, but also offers several pre-trained models such as VGG-Face and FaceNet. This provides flexibility in choosing the model that best fits the needs of our project in terms of accuracy and computational efficiency. For this project, we have opted for VGG-Face due to its consistent performance. Given that our program is primarily coded in Python, DeepFace's Python-based architecture ensures easy compatibility with the simulation environment.

D. Compare the Performance of Collaborative Filtering Model Implemented SVD and ALS Model

In this study, we evaluate the performance of two collaborative filtering models: one implemented using Singular Value Decomposition(SVD) and the other utilizing the Alternating Least Squares (ALS) algorithm. We compare the performance of these models against a baseline performance. The described scenarios will be implemented using Python 3 in a Jupyter Notebook environment, leveraging TensorFlow tensors, the Keras API, and the base models from the AlternatingLeastSquares library.

Baseline performance formulas:

$$\text{Precision} = \frac{|\text{Popular Items from Training dataset} \cap \text{Actual Bought Items from Test Set}|}{|\text{Popular Items from Training dataset}|} \tag{7}$$

$$\text{Recall} = \frac{|\text{Popular Items from Training dataset} \cap \text{Actual Bought Items from Test Set}|}{|\text{Actual Bought Items from Test Set}|} \tag{8}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

E. Compare the Performance of Similarity Calculations Between Content-Based Filtering Model and ALS Model

We also compare the performance of similarity calculations between products obtained from the Content-Based Filtering (CBF) model and the ALS model. The product embeddings from both models were used to calculate product similarities. We compare the performance of similarities based on the ground truth that products from the same aisles are considered the most similar. The described scenarios will be implemented using Python 3 in a Jupyter Notebook environment, leveraging TensorFlow tensors, the Keras API, and the base models from the AlternatingLeastSquares library.

F. New User Signup, Survey, and Recommendation Path

In this scenario, we simulate the journey of a new user from the initial signup process to receiving personalized product recommendations using our frontend application.

1) User Signup Process: When a new user visits the system, they can sign up by providing basic information and uploading a profile picture. The user is prompted to enter a username and can either upload a profile picture or use the app's camera to take a photo. This photo is saved to Firebase with the username as the filename and will be used for facial recognition during the login process. The uploaded or captured photo is processed using a facial recognition system to detect the user's mood, which plays a crucial role in personalizing product recommendations.

2) User Login Process: After signing up, the user can log in by uploading a photo or using the app's camera to take a new one. The system processes this photo by comparing it with the saved photos in Firebase to recognize the user. Once identified, the detected mood is also recorded.

3) User Preference Survey: Upon successful login, the user is guided to the preference survey. This survey gathers information about the user's preferences and interests to tailor product recommendations. The survey includes a list of the top 50 product aisles based on purchase counts from our dataset, and users select the aisles they are interested in. The responses are collected and processed to generate relevant recommendations.

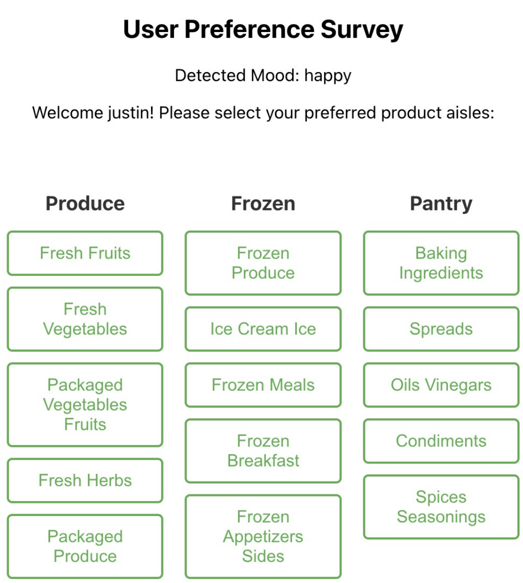


Fig. 4: User Preference Survey

4) Recommendation Path: Based on the user's survey responses and detected mood, the system generates a comprehensive recommendation list consisting of three types of recommendations: initial recommendations, mood-related recommendations, and close-to-expiration recommendations (Figure 5). The initial recommendations consider the user's interests and the most popular products in the selected categories. The mood-related recommendations are tailored to match the user's current emotional state and interests. The close-to-expiration recommendations help users find timely deals and reduce food waste by highlighting products that are nearing their expiration dates.

Recommendations

Initial Recommendations

Product Name	Aisle	Department
100% Whole Wheat Bread	bread	bakery
Large Alfresco Eggs	eggs	dairy eggs
Bag of Organic Bananas	fresh fruits	produce
Organic Bread with 21 Whole Grains	bread	bakery
Organic Grade A Free Range Large Brown Eggs	eggs	dairy eggs

Mood Related Recommendations

Product Name	Aisle	Department
Blended Vanilla Lowfat Yogurt	yogurt	dairy eggs
Oikos Toasted Coconut Vanilla Greek Yogurt	yogurt	dairy eggs
Nonfat Vanilla Greek Yogurt	yogurt	dairy eggs

Close to Expiration Recommendations

Product Name	Aisle	Department
Small Walnut Levain Bread	bread	bakery
Great White Bread	bread	bakery
Organic Plain French Style Yogurt	yogurt	dairy eggs

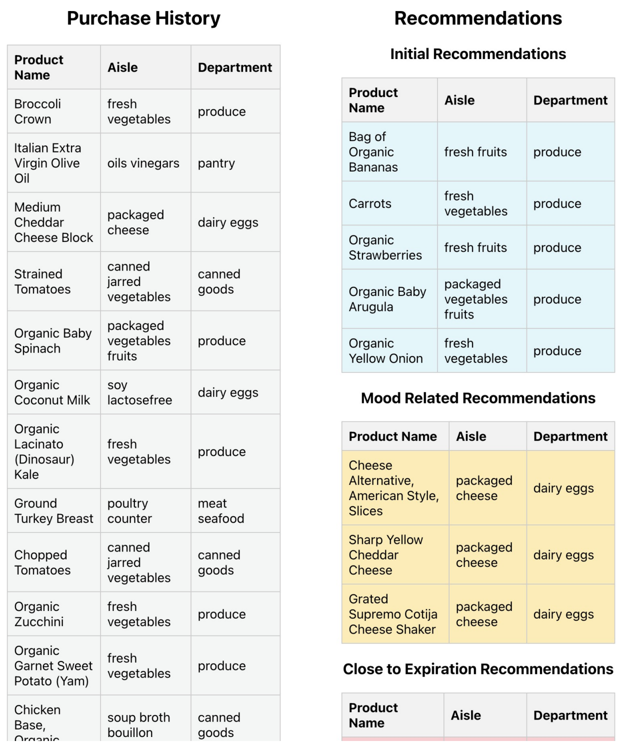
Fig. 5: Recommendations To New User

G. Existing User Login and Recommendation Path

In this scenario, we simulate the process for an existing user logging into the system and receiving personalized product recommendations based on their historical data and current mood.

1) User Login Process: An existing user begins by logging into the system using either an uploaded photo or the app's camera to take a new photo. The system processes this photo by matching it with the stored images in Firebase to identify the user. Upon successful identification, the system also detects the user's current mood through facial recognition technology. This mood detection is integral for tailoring the product recommendations to better suit the user's current emotional state.

2) Recommendation Generation: Once the user is logged in and their mood is detected, they proceed to the "Get Recommendations" page in the application. Here, they input their user ID, detected mood, and the desired number of recommendations. The system then generates a comprehensive recommendation list. The list includes initial recommendations based on the user's historical purchase data, mood-related recommendations tailored to the user's current emotional state, and close-to-expiration recommendations to promote sustainability and reduce food waste. Additionally, the system provides a list of the user's purchase history, allowing for a direct comparison between past purchases and the new recommendations (Figure 6).



Purchase History

Product Name	Aisle	Department
Broccoli Crown	fresh vegetables	produce
Italian Extra Virgin Olive Oil	oils vinegars	pantry
Medium Cheddar Cheese Block	packaged cheese	dairy eggs
Strained Tomatoes	canned jarred vegetables	canned goods
Organic Baby Spinach	packaged vegetables fruits	produce
Organic Coconut Milk	soy lactosefree	dairy eggs
Organic Lacinato (Dinosaur) Kale	fresh vegetables	produce
Ground Turkey Breast	poultry counter	meat seafood
Chopped Tomatoes	canned jarred vegetables	canned goods
Organic Zucchini	fresh vegetables	produce
Organic Garnet Sweet Potato (Yam)	fresh vegetables	produce
Chicken Base, Organic	soup broth bouillon	canned goods

Recommendations

Initial Recommendations

Product Name	Aisle	Department
Bag of Organic Bananas	fresh fruits	produce
Carrots	fresh vegetables	produce
Organic Strawberries	fresh fruits	produce
Organic Baby Arugula	packaged vegetables fruits	produce
Organic Yellow Onion	fresh vegetables	produce

Mood Related Recommendations

Product Name	Aisle	Department
Cheese Alternative, American Style, Slices	packaged cheese	dairy eggs
Sharp Yellow Cheddar Cheese	packaged cheese	dairy eggs
Grated Supremo Cotija Cheese Shaker	packaged cheese	dairy eggs

Close to Expiration Recommendations

Product Name	Aisle	Department

Fig. 6: Recommendations To Existing User

VI. Results

A. Face Recognition and Emotion Detection Performance

Based on previous studies, DeepFace has demonstrated exceptional accuracy in face recognition tasks, achieving a 97.35% accuracy on the Labeled Faces in the Wild (LFW) dataset [35]. This high level of accuracy underscores its robustness and reliability in facial recognition applications.

In our own manual testing, the program successfully identified each user's face among our team members. However, accuracy decreases when obstructions such as masks or hats partially cover the face. The system effectively detects explicitly expressed emotions. Yet, in cases where facial expressions are more nuanced, the accuracy of emotion detection diminishes. For instance, a surprised expression might be recognized as neutral if the mouth is not widely open.

B. Machine Learning Models Performance

In this part, we present the evaluation results of our collaborative filtering models in comparison with the baseline. The performance metrics used for evaluation are precision, recall, and F1 score. The results are summarized in Table II.

Based on our studies, the collaborative filtering model based on the Alternating Least Squares (ALS) algorithm achieves a precision of 1.89%, a recall of 4.19%, and an F1 score of 2.26%. These results demonstrate that the ALS model outperforms both the baseline and the gradient descent model. The higher precision and recall values indicate that the ALS model is more effective at identifying relevant items, leading to a substantially improved F1 score.

	Precision	Recall	F1_score
Baseline Model	1.31%	2.64%	1.52%
SVD	0.55%	1.31%	0.67%
ALS	1.89%	4.19%	2.26%

TABLE II: Performance comparison of different models. All results are obtained from the purchase frequency dataset, which consists of three columns: user_id, product_id, and purchase_count. The training dataset contains 13,307,953 rows and the test dataset has 1,384,617 rows.

Additionally, we also compare the performance of finding similar products using product embeddings from our models. This comparison helps to understand how effectively the models can identify similar products based on their embeddings. The performance metrics used for this evaluation are the same: precision, recall, and F1 score. The results are summarized in Table III.

	Precision@10	Recall@10	F1_score@10
ALS	26%	0.62%	1.2%
CBF	99.8%	2.68%	5.11%

TABLE III: Performance comparison of finding similar products using product embeddings.

The comparison of finding similar products reveals that the CBF model significantly outperforms the ALS model. The CBF model achieves a precision of 99.8%, indicating that nearly all the top-N similar products identified by this model are indeed from the same aisle as the given product. This high precision is complemented by a recall of 2.68% and an F1 score of 5.11%, suggesting that the CBF model is not only precise but also effective in capturing a significant portion of the true similar products. In contrast, the ALS model, while still performing better than random chance, shows considerably lower precision, recall, and F1 scores.

C. User Feedback Survey Analysis

To assess the effectiveness of our emotion detection and recommendation system, we designed and conducted a survey among prospective users. Given the subjective nature of evaluating the relevance of recommended items, the survey aimed to grade the system's performance. The survey was conducted in two scenarios: new users and existing users. New users followed the signup, survey, and recommendation path, while existing users were given recommendations based on their purchase history. Participants rated the accuracy of emotion detection, the relevance of recommendations to their preferences, and the impact of these recommendations on their purchasing decisions. We also collected suggestions for further improvements to enhance our system. The following results outline key findings from the survey and highlight areas for future enhancements.

The survey on our recommendation system reveals overall positive results, demonstrating its effectiveness in both emotion detection and product recommendation. Participants rated the emotion detection with an average score of 3.98

out of 5, indicating that the system can accurately interpret emotional cues. Figure 7 illustrates the user feedback on emotion detection.

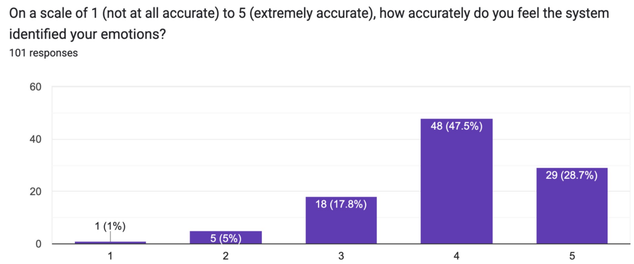


Fig. 7: Emotion Detection User Feedback

New users noted a high relevance of the product recommendations to their preferences, giving an average relevance rating of 4.35 out of 5. Existing users, however, rated the relevance of recommendations based on their purchase history slightly lower, at 3.89 out of 5. This difference is likely due to the smaller subset of existing users and the diverse range of available items compared to their limited purchase history. Figure 8 and Figure 9 illustrate the user ratings for the relevance of the products recommended.

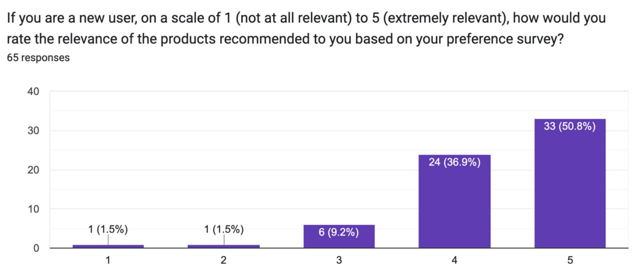


Fig. 8: Recommendation Relevance Feedback From New Users

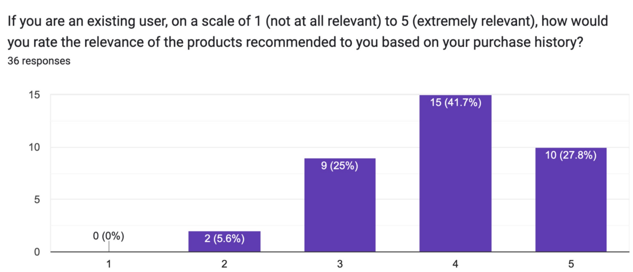


Fig. 9: Recommendation Relevance Feedback From Existing Users

We also asked users about their satisfaction with the system's product recommendations. As Figure 10 illustrates, satisfaction was generally high, with 79.21% of users rating their satisfaction at 4 or higher. This reflects a positive reception of the recommendation system, and indicates that our system

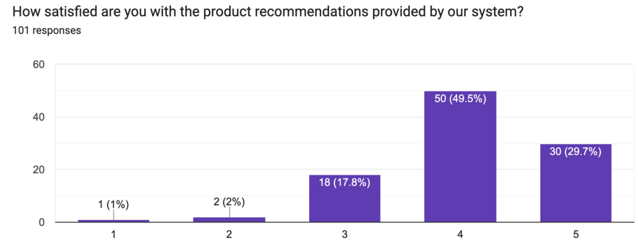


Fig. 10: Overall Recommendation Satisfaction

is effective in delivering relevant and satisfactory product recommendations.

90.10% of respondents reported that the recommendations influenced their purchasing decisions, predominantly increasing their likelihood of purchases, with 78.2% stating they were more likely to buy the recommended items. Figure 11 and Figure 12 illustrate the details.

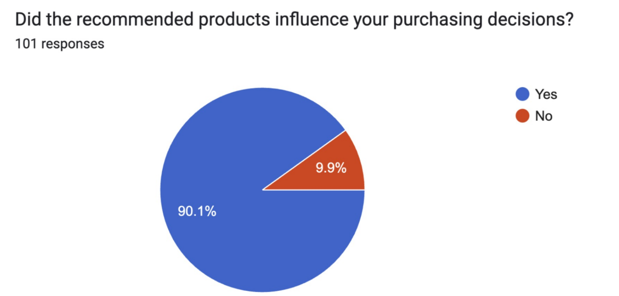


Fig. 11: Influence Of Recommendations On Purchasing Decisions

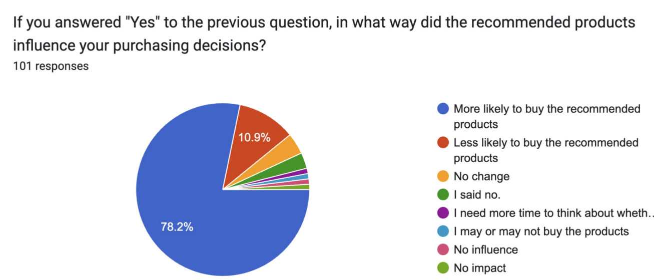


Fig. 12: Nature Of Influence On Purchasing Decisions

In the final part of our survey, we collected suggestions for improving our system. The feedback included recommendations for suggesting seasonal produce, reducing the number of recommendations to prevent decision fatigue, enhancing emotion recognition accuracy, and incorporating a preference survey for existing users. These insights offer valuable guidance for future system enhancements.

To sum up, the survey results suggest that our emotion detection and recommendation system performs well in terms of emotional accuracy and the relevance of recommendations. New users generally found the recommendations to align well with their preferences, while existing users rated the relevance slightly lower, which may reflect the limitations of their purchase history. Overall satisfaction with the system was high, and many users reported that the recommendations positively influenced their purchasing decisions.

VII. Limitation and Future Work

A. Face Recognition and Emotion Detection

Our program offers two methods for user identification: via camera or by uploading a photo. It is designed to process the dominant presence of a person captured on camera, based on the face's size and position in the image. Detection accuracy decreases with multiple faces, as DeepFace performs optimally with single-person identification. In addition, the program performs best when faces are viewed from the front, similar to a profile picture. Accuracy is reduced for side angles or tilted positions. However, this limitation does not impact the photo upload functionality, which requires users to upload a profile image with only one person present. Our face detection also assumes that there are no obstructions or coverings over the face. Items like hats and masks can significantly reduce the accuracy of both face identification and emotion detection. Furthermore, our emotion detection system is limited to recognizing explicitly expressed emotions and may struggle with nuanced facial expressions.

B. Recommendation System

Due to dataset limitations, our dynamic pricing currently focuses solely on expiration dates and lacks integration with real-time inventory data and market demand analysis, which limits its optimization potential. The system's reliance on historical purchase data from a single source also constrains the accuracy of its recommendations. Additionally, the recommendation system we built is static, as it cannot incorporate real-time user feedback or adapt effectively to evolving user preferences and behaviours over time.

C. Future Work

Future research can focus on several key areas to advance both the face recognition and emotion detection system, as well as the recommendation system. One area of focus will be enhancing the system's ability to process images with multiple faces or taken from various angles and to recognize nuanced or subtle emotional expressions. One potential solution is to transition from analyzing static images to processing video clips, which could improve detection accuracy. Another area of focus is making the recommendation system dynamic by allowing users to provide live feedback on recommended products, enabling the system to adapt and improve. A significant limitation of our current dataset is the absence of information on prices and stock levels. If we were provided with such datasets, we could further enhance our model.

VIII. Conclusion

In this paper, we present a novel approach to developing supermarket recommendation systems by integrating multiple components, including customer emotions, purchase history, and product shelf life. Our hybrid recommender system combines Collaborative Filtering and Content-Based Filtering to deliver personalized and dynamic recommendations tailored to each customer's preferences and current emotional state.

Our results demonstrate the effectiveness of this hybrid approach, with the ALS model outperforming traditional SVD methods in terms of precision, recall, and F1 score. The Content-Based Filtering model is highly effective at identifying similar products, further enhancing the recommendation process. When combined with emotion detection and promotions for products nearing expiration, our system achieves higher overall customer satisfaction and would increase willingness to purchase.

In conclusion, our research advances machine-learning-based supermarket recommendation systems, offering a more dynamic and personalized shopping experience. This approach not only caters to customer preferences but also promotes sustainability through effective management of expiring products.

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