2.2.1.1 Comparison Table

Feature	**ARoma**	**Toast POS**	**Kounta**	**QikServe**
AR Meal Preview	✅	❌	❌	❌
Allergen Filtering	✅	❌	❌	❌
Real-Time Order Tracking	✅	✅	✅	✅
Menu Customization	✅	✅	✅	✅
Feedback Integration	✅	✅	✅	✅

Comparison Table

2.2.2. Literature Review: machine learning models for menu item recommendation system.

Content-based filtering

Content-based filtering works by analyzing the characteristics of items and users' preferences when giving recommendations. In Aroma, this technique will go a long way toward improving customer experiences through the delivery of personalized recommendations, laying its foundation on user behavior and item attributes. The following fully explains how Aroma will apply this technique in content-based filtering:

(i) How to Use Content-Based Filtering on Aroma
CBF bases recommendations on the similarity between item features and a user's profile. In the case of Aroma, it can be implemented as follows:

1. Feature Extraction:
Items-food/drink/restaurant names:
Extract such features such as type of food-for example, Italian, Indian; price range; dietary options such as vegetarian, gluten-free; restaurant location/rating.

Users:

User profiling will be done by studying users' past interactions-like previously ordered dishes, cuisines frequently chosen, restaurants visited, or any other preferences.
Include explicit preferences, such as a user stating they do not like spicy food.

2. Similarity Metrics:
The similarity between items and the user's taste may be calculated by any similarity measures, such as Cosine Similarity or Euclidean Distance.
Suggest, for instance, an Italian dish to a user who has ordered Italian very frequently before.

3. Algorithm Implementation:
Use vectorization techniques for the attributes of items and user profiles by methods like TF-IDF, or one-hot encoding.
Similar computation can be done by libraries such as Scikit-learn, TensorFlow, or Surprise.

4. Recommendation Process:
Match user profile with the database of restaurant/dish items ranked in order from highest to lowest similarity score.

(ii) Why Content-Based Filtering is a poor choice for Aroma
While CBF might work in some context, there are quite a few drawbacks, especially with regards to a platform like Aroma, which addresses restaurants, menus, and customers. Here's why:

1. Cold Start Problem:
New Users: If he is a new user who has never interacted, the system is unable to recommend items using only the preference previously given.
New items: No new items related to dishes or restaurants should be recommended unless clearly tagged to the users' interactions or preferences.

2. Over-specialization
CBF tends to recommend items similar to what the user has already interacted with, reducing diversity in suggestions. For example, a user who orders Indian food might never discover trending Mexican dishes.

3. Absence of Social Discovery:
Because CBF does not take as input the preference of other users, it cannot recommend popular or highly rated items across a larger population.

4. Limited cross-user insights

Aroma's success is in the capturing of the trends and the collective user behavior, such as dishes trending across customers in a certain city. CBF cannot account for that.

5. Scalability Issues:
Computing pairwise item similarity for all items has become computationally expensive with the ever-growing number of items and users.

6. No dynamic context awareness.
CBF doesn’t consider factors like time of day, user mood, or real-time trends, limiting the relevance of recommendations.

(iii) Why a Hybrid Model is Better than Content-Based Filtering
The hybrid model overcomes the weaknesses of CBF through a hybrid combination with collaborative filtering, knowledge-based recommendations, and probably deep learning-based models. The hybrid approach would be more suitable for Aroma because of the following reasons:

1. Eliminates Cold Start Problems
New Users: These make recommendations for new users with no past records, basing this on the preference of similar users through collaborative filtering.
New Items: Either popularity-based or rule-based approaches within a hybrid model make sure that new items are recommended.

2. Recommendation Diversity Increases
It mixes content-based recommendations, such as "Similar Cuisine," with collaborative suggestions, like "People who like this also like…," to make sure users are always finding new and different things.

3. Provides social insights, collaborative
CF analyzes the trend preference of all users such as:
Trending restaurants or dishes.
High-rated products in a particular niche.

4. Context and Popularity Awareness
Aroma may include real-time trending, such as:
Things normally taken for breakfast.
Trending restaurants on weekends.

5. Greater Accuracy, Higher Personalization The model couples the precision of Content-Based Filtering in matching user preference with the exploration power of Collaborative Filtering, hence giving better personalization and a more serendipity-based recommendation system.

6. Example Workflow: Hybrid Model for Aroma User's History-based (Content-Based) Suggest dishes by the most ordered cuisine or preferential taste. Similar Users (Collaborative Filtering): Suggest items popular among customers with similar tastes or ordering behavior. Business Rules and Trends: Suggest trendy restaurants or new dishes even if the users have never interacted with each other.

7. Hybrid Advanced Techniques Weighted Hybrid: Combine the scores from content-based and collaborative filtering. Example: 70% Content - 30% Collaborative. Switching Hybrid: Content-based for new users, collaborative for advanced users. Deep Learning: The realization of Neural networks for content-based, collaborative, and context-aware features. Use of LSTMs for time-aware recommendations.

Collaborative filtering

Collaborative Filtering (CF) predicts user preferences based on known item ratings and is a key method for recommendation systems. It addresses information overload by tailoring suggestions. By customizing recommendations, it tackles information overload. (Zhang et al., 2014).

This review focuses on current collaborative filtering (CF) techniques for predicting food preferences based on user behavior and past interactions. It highlights challenges such as data sparsity, cold-start problems, and difficulties in addressing dietary needs. To improve accuracy, the review suggests integrating contextual factors and combining CF with content-based filtering and hybrid methods for better personalization.

In order to predict food preferences based on user behavior and previous interactions, this review looks at the collaborative filtering (CF) methods currently in use for food recommendations. It draws attention to issues like cold-start issues, data sparsity, and challenges in meeting dietary requirements. In order to increase accuracy, the review also highlights shortcomings in current systems, highlighting the need for more contextually relevant recommendations and combining CF with other techniques, such as content-based filtering and hybrid approaches.

Overview of Collaborative Filtering

There are two primary methods for collaborative filtering (CF): memory-based (which emphasizes similarity metrics) and model-based (which uses matrix factorization). Although matrix factorization frequently yields higher accuracy, it has drawbacks, including local optima during learning. Better similarity metrics help memory-based CF, but robust predictive models are needed to provide accurate recommendations. To improve prediction accuracy and identify patterns in user-item interactions, methods such as deep learning and k-nearest neighbors are employed (Zhang et al., 2014).There are two categories of memory-based collaborative filtering (CF): item-based and user-based. User-based CF looks for users who share similar tastes and makes product recommendations based on these users' ratings. By examining patterns of behavior, it customizes recommendations. In contrast, item-based CF looks for items that are comparable to the one the user is currently rating. Based on how similar an item is to other items the user has rated, it forecasts the user's interest in that item (Chen et al., 2018).

Applications in Food Preferences which use CF

A restaurant recommendation system that utilizes Zomato reviews to make food recommendations based on user preferences is described in the paper by M. Goel et al. After identifying popular dishes and analyzing customer sentiment from reviews, the system uses collaborative filtering to generate suggestions. One of the system's main drawbacks, though, is that some dataset features are underutilized, which limits the scope of the analysis. Together with the reviews, these underutilized features might offer a more complete recommendation system.

Li Chen et al. combined content-based techniques, collaborative filtering, and product rating preferences to create a user-reviewed restaurant recommendation system. The system uses user-provided ratings to display restaurants and uses text analysis to examine customer reviews. One drawback of the system is that it can't simultaneously sort restaurants by rating and location, which limits its ability to provide tailored suggestions.

Challenges in CF for Food Preferences

The application environment gets increasingly complex, the data types get increases, the data volume rises, and the main issues with the current algorithms are as follows:

1.Cold start problem: Collaborative filtering (CF) algorithms have a hard time producing reliable recommendations when new users or food items are introduced because there is a lack of data. The system's capacity to make pertinent recommendations is hampered by data gaps caused by the absence of ratings for new food items or past preferences from new users (Chen et al., 2018).

2.Sparsity: The user-item interaction matrix in CF is sparse since the majority of users only rate a small portion of the available items. The effectiveness of the recommendations is decreased by the inability to identify patterns between users and items due to the lack of adequate data (Chen et al., 2018).

3.Contextual factors: External factors that are crucial for individualized food recommendations, such as allergies, dietary restrictions, or cultural preferences, are frequently difficult for CF to account for. If these are not taken into consideration, the user may receive recommendations that are inappropriate or irrelevant(Chen et al., 2018).

The cold start problem, sparse data, and the challenge of integrating contextual factors like dietary restrictions or allergies are some of the issues that collaborative filtering (CF) faces. While memory-based CF is commonly used, model-based techniques like matrix factorization offer better accuracy. Improvements in similarity metrics, hybrid approaches, and incorporating contextual factors are required to improve CF performance (Zhang et al., 2014; Chen et al., 2018).

Hybrid model

According to Thorat, Goudar, and Barve (2015), hybrid recommender systems combine two methods which are collaborative filtering (CF) and content-based filtering (CBF). hybrid models integrate both techniques to enhance recommendation accuracy by overcoming the individual weaknesses of each CF and CBF models.

Collaborative filtering (CF) struggles in cases where there is little data, a problem known as the 'cold start' issue. This can cause problems for apps in the early stages, or for small businesses with limited customer bases, as there may not be enough interactions to generate meaningful recommendations.

Content based filtering (CBF) recommends items based on their features, characteristics or keywords the user has shown interest in. However this approach also is limited because it only suggests items that are similar to what the user has already interacted with. Which keeps the user in a narrow range of recommendation.

Therefore, the hybrid model is the best approach for aroma, as content-based filtering (CBF) can recommend items based on dietary restrictions, while collaborative filtering (CF) can suggest complementary food combinations by identifying popular or frequently bought items.

2.2.3 Literature Review: Augmented Reality (AR) in Food Preview Systems

2.2.3.1 Introduction

Augmented reality is gradually becoming an important technology that is changing the food and hospitality industry. AR-based food preview systems enable restaurants to provide interactive, immersive, and engaging customer experiences. This review examines the current state of AR adoption in restaurants, focusing on applications, benefits, challenges, and future directions

2.2.3.2 Applications of Augmented Reality in Restaurants

The implementation of AR in restaurants has primarily revolved around enhancing customer interaction through dynamic visualizations .Studies have explored its use in the following key areas:

1. AR based food menus :

   These AR-powered menus would show 3D models of dishes which helps customers to visualize the food before ordering . Patel et al. (2024) highlight the potential of AR menus to provide detailed information on portion size, textures, and nutritional data, thereby improving decision-making.

2. Interactive Ordering Systems

   Mali et al. (2021) discuss the integration of AR into ordering systems,where the QR-code-driven AR interfaces enable customers to order their food easier and erase language barriers.

3. Food Presentation and Desirability

   Fritz et al. (2022) demonstrated that AR enhances food desirability by enabling customers to mentally simulate food consumption by viewing superimposed images , which would increase purchase likelihood

4. Training and Staff Engagement: