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Intelligent Food Recommender Systems Literature Review

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Abstract

Food Recommender Systems (FRS) has emerged as an important sub area of Computer Science and Engineering (CSE) that is significantly different from other traditional areas of recommendation such as e-commerce or media streaming. This systematic review aims to do an architectural analysis of intelligent FRS using Artificial Intelligence (AI) and Machine Learning (ML). We summarize 21 basic peer-reviewed studies and examine how these emergent systems cope with high dimensional and non-linear constraints like user health states, complex multi-component ingredients, temporal consumption rules, and multimodal streams of features. These methods fall into four structural paradigm groups: Traditional Matrix Methods, Sequence-based Neural Nets, Heterogeneous Information Networks (HIN), and Advanced Optimization Frameworks. Last, open challenges for sparsity training, cold-start issue and unified offline metrics for algorithmic precision nutrition are elaborated which will serve as future research roadmap.

Keywords: Food Recommender Systems, Heterogeneous Information Networks, Deep Learning, Multi-Objective Optimization, Computational Health.

1. Introduction

For Computer Science engineers, it is very challenging to create a strong Food Recommender System (FRS). While the user-item interaction in normal recommendation scenarios may be very simple (match a user with a film or a book), in the case of food recommendations, numerous non-static and sometimes conflicting factors must be addressed. Optimizing for user preference alone is not enough to optimize a system, because if it is, the system will surface items high in sugars or saturated fats, which have negative long term health feedback loops (EL Majjodi, 2025). Rather, modern FRS needs to navigate complex layers of data, encompassing culinary choices, biometric readings, allergies and unique bodily requirements.

Food items are, in fact, complex multi-component data nodes, from a CSE infrastructure standpoint. A single dish is not a single product, it is an ensemble of different raw products having their own chemical, preparation and nutritional vectors. This complex nature leads to significant data sparsity and intricate relational relationships, making conventional collaborative filtering methods unsuitable (Chow, 2023; Tsolakidis et al., 2024).

To clearly demarcate this domain, this systematic review focuses on the common food architecture models available to represent food data, sets up clear performance comparisons with modern models and offers an exportable reference catalog to simplify future research pipelines.

2. Methodology & Model Architectures

Conventional intelligent food recommendation systems can be categorized by four basic architectures according to the type of data topology and the type of machine learning tasks.

2.1 Introduces support for traditional filters and hybrid baselines.

The initial versions of FRS use collaborative filtering (CF) or content-based filtering (CB) matrices as an approximation to user preference configurations. Content-based structure-based surface is based on explicit recipe profiles (e.g., cooking time, regional style, main protein) to expose items that are structurally similar to a user's top-rated history (Arulprakash et al., 2024). Collaborative frameworks, on the other hand, use matrix factorization (MF) or singular value decomposition to identify unknown preference dimensions shared by common signatures of user interactions (Chow, 2023).

These basic systems are efficient for computation but are sensitive to the high degree of data sparsity found in culinary data, which causes a serious "cold-start" issue when presented with out-of-sample regional cuisines or users.

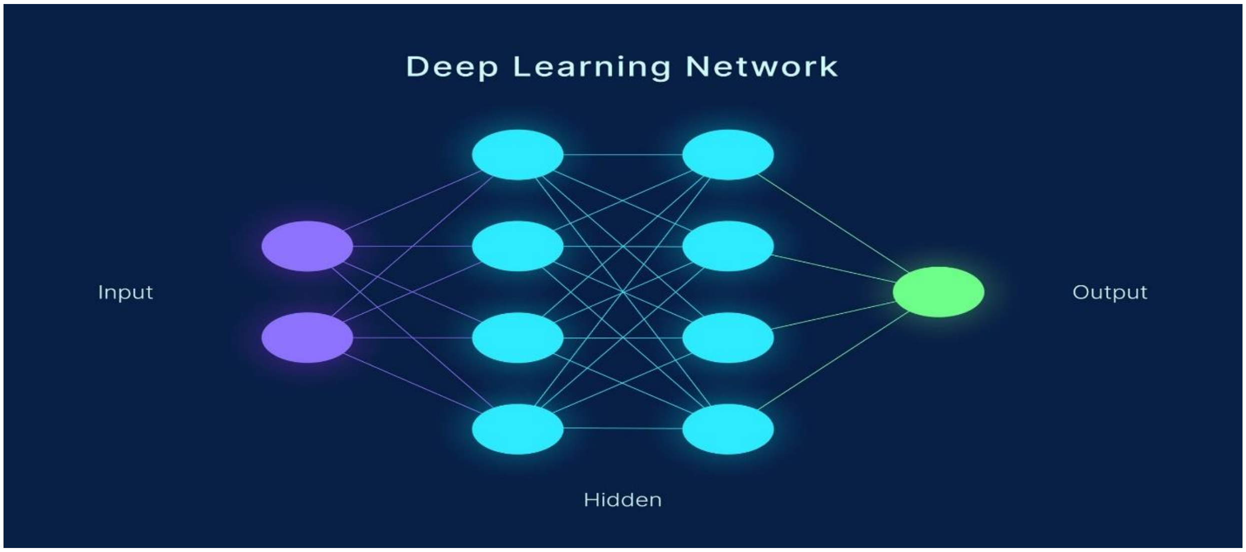
2.2 Sequence-Based Deep Neural Networks

Because food choice varies over chronological periods (e.g., breakfast versus dinner profiles and seasonal changes, as well as fatigability over consecutive days), engineers employ recurrent architectures for handling the temporal dependency. These models combine traditional Deep Neural Networks (DNN) for handling static information like long-term food allergies or demographic details, with stacked Long Short-Term Memory (LSTM) layers or Gate Recurrent Units (GRU) for processing temporal dietary logs (Karunasri, 2026; Liu et al., 2023).

These models measure a user's current history one step at a time and provide real-time personalized recommendations based on recent consumption, thus avoiding menu fatigue and adapting to varying energy needs.

2.3 HINs and Graph Attention Layers are introduced in the realm of heterogeneous information networks.

The ‘state-of-the-art' paradigm of FRS is to consider the data as a multi-relational graph $G = (V, E, C)$, where node types (V): Users, Recipes, Ingredients, Nutrients, are independent entity classes linked by semantic edges (E). The system enables engineers to map interactions that transcend the user-item entity model, as seen in Tian et al. (2022).



These types of graph spaces are equipped with Hierarchical Graph Attention Networks (HGAT) (Tian et al., 2022) to extract high order path semantics. The type-specific transformation matrices transform the different types of data into a common latent space. After alignment, the attention layers at node-level and relationship-level dynamically adjust the weights for neighboring entities. This allows the system to adjust a user's personalized taste experience with the objective health rules without skewing the significant nutritional relationships in embedding steps (Forouzandeh et al., 2024).

To improve these graph models, when data is limited, Cross-View Heterogeneous Graph Contrastive Learning (CGHF) (Wang & Zheng, 2025) is incorporated. This method trains two network pipelines, one based on a user-interaction view and the other based on a structural ingredient-nutrition view, to learn recommendations that are both accurate to taste and consistent with the fundamental nutrition rules.

2.4 To solve multi-objective optimization and constraint problems.

If the FRS needs to deal with hard health care or sporting requirements, it views recommendation as a multiple-objective optimization problem. These frameworks utilize Multi-Objective Evolutionary Algorithms Based on Decomposition (MOEA/D) for the optimization of recipe configurations in multiple nutritional limits at the same time (Huang et al., 2024). Instead of a rank-based approach, these architectures identify a Pareto-optimal set, which is a region of solutions that are not dominated by other solutions in terms of diversity and visual appeal, even when the objective is to optimize the diversity of the menu and its visual appeal, but the constraint is complex, such as reducing sodium or avoiding specific allergens (Wang 2026).

3. Comparative Analysis

The table below compares the four core architectural paradigms used in modern intelligent Food Recommender Systems across data requirements, algorithmic strengths, and primary deployment limitations.

Algorithmic Paradigm	**Core ML/AI Models**	**Primary Computational Input**	**System Advantages**	**Core Engineering Limitations**
Traditional Filtering & Hybrid Baselines	Matrix Factorization, Cosine Similarity, SVD	Pairwise User-Item rating arrays, flat text ingredient tags	Low runtime latency, simple implementation pipelines, clean mathematical interpretation	Severe cold-start issues, fails to capture multi-component recipe data structures
Sequence-Based Neural Networks	Stacked LSTMs, GRUs, Deep Neural Networks (DNN)	Chronological user meal logs, continuous biometric sensor data streams	Adapts to daily cravings and menu fatigue, tracks changing user preferences	Demands high-volume, sequential datasets; high training footprint
Heterogeneous Information Networks	HGAT, Contrastive Learning (CGHF), Knowledge Graphs	Multi-relational graphs (V_U, V_R, V_I, V_N), typed meta-paths	Learns deep, high-order relations; reduces data sparsity via feature propagation	Complex graph construction and alignment phases; high memory use at scale
Multi-Objective Optimization	MOEA/D, Evolutionary Solvers, Rank Engines	Clinical nutrition guidelines, allergen matrices, user target goals	Ensures strict constraint compliance, handles complex health profiles	Computationally expensive optimization phases; heavily reliant on clean rule tables
Reference	Primary CSE Domain / Focus	Core Algorithmic Framework	Key Dataset(s) / Data Inputs Used	Primary Evaluation Metrics

4. Open Engineering Challenges

Although some of these performance improvements have been achieved across different graph and deep learning architectures, there are three engineering pain points that have been identified from the systematic literature reviews:

The first challenge is that smoothly integrating computer vision pipelines (which were employed to segment food-logs automatically) into the underlying graph attention embeddings is challenging. The lighting conditions, such as slight changes or complex and mixed food items, cause feature errors that reduce the accuracy of the downstream recommendations (Qiao et al., 2025).

Secondly standard accuracy measurement metrics (such as Precision and Recall) do not reflect important clinical attributes such as menu safety, overall dietary balance and user adherence in the long term (Theodoridis et al., 2019) and Finally Biometric Integration Latency: Scalable, secure systems that can manage real-time physiological telemetry (such as continuous glucose reading) without causing huge data processing delays is still a systems challenge (Agrawal, 2026).

5. Conclusion

While the flat matrix setups are being abandoned in favor of rich multi-relational graphs and sequential deep learning models in Intelligent Food Recommender Systems. Modern systems can capture high-order relationships across users, compound recipes and granular nutrient fields, all represented as an interconnected Heterogeneous Information Network. This structural change gives the developers the flexibility to consider a user's own preference choices as well as hard science health guidelines. In the future, the discipline can be enriched by guiding research towards common multi-objective evaluation metrics and well-designed multimodal pipelines, which integrate computer vision logs with the fundamental knowledge graph skeletons together.

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