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Dedication

I dedicate this thesis with all my love and gratitude:

To my extraordinary parents, whose endless sacrifices, unwavering love, steadfast support, and heartfelt prayers have been the foundation of my journey and the light that guided me through every challenge.

To my beloved sisters, my dear aunt, and my best friend, your constant encouragement and unconditional support have been my strength and comfort. Thank you for standing by me, every step of the way, inspiring me to persevere and grow.

Abstract

Nowadays, food recommendation systems play a crucial role in promoting healthy eating behaviors. They assist individuals in making more informed dietary choices that align with their personal needs and preferences. Given the complexity of food selection, influenced by factors such as nutritional content, personal habits, and health goals, there is a growing need to develop intelligent systems capable of effectively supporting users in this decision-making process. Despite recent technological advances in recommendation systems, many traditional approaches still rely primarily on users' past preferences and ratings, often overlooking the nutritional and health aspects of the recommended foods. This limitation hinders their ability to effectively support users in achieving their health-related objectives. To address this issue and strive for a balance between user preferences and health considerations through a fair and health-conscious recommendation strategy, we initially employed the NeuMF model to predict user preferences. In this approach, we integrated ingredient data and a health score to generate dietary recommendations that account not only for prediction accuracy but also for compliance with health standards. We also applied the NeuMF model a second time, this time excluding the health score and relying solely on ingredients. After this initial prediction, we used a linear function to combine the model's output with the health score, aiming to produce recommendations that balance personal preferences with nutritional benefits. Striking this balance proved to be a significant challenge, as placing too much emphasis on health aspects can reduce user satisfaction and the overall effectiveness of the system.

Keywords: Food Recommendation System, Personalized nutrition, Healthy eating, NeuMF, Deep Learning.

Résumé

De nos jours, les systèmes de recommandation alimentaire jouent un rôle crucial dans la promotion de comportements alimentaires sains. Ils aident les individus à faire des choix alimentaires plus éclairés, en accord avec leurs besoins et préférences personnels. Étant donné la complexité du choix alimentaire, influencé par des facteurs tels que la composition nutritionnelle, les habitudes personnelles et les objectifs de santé, il est de plus en plus nécessaire de développer des systèmes intelligents capables de soutenir efficacement les utilisateurs dans ce processus décisionnel. Malgré les avancées technologiques récentes dans les systèmes de recommandation, de nombreuses approches traditionnelles s'appuient encore principalement sur les préférences et évaluations passées des utilisateurs, négligeant souvent les aspects nutritionnels et sanitaires des aliments recommandés. Cette limitation nuit à leur capacité à aider efficacement les utilisateurs à atteindre leurs objectifs en matière de santé. Pour remédier à ce problème et viser un équilibre entre les préférences des utilisateurs et les considérations de santé à travers une stratégie de recommandation équitable et soucieuse de la santé, nous avons d'abord utilisé le modèle NeuMF pour prédire les préférences des utilisateurs. Dans cette approche, nous avons intégré des données sur les ingrédients, et un facteur de santé afin de générer des recommandations alimentaires tenant compte à la fois de la précision des prédictions et du respect des normes sanitaires. Nous avons également appliqué une seconde fois le modèle NeuMF, cette fois sans le facteur de santé, en nous basant uniquement sur les ingrédients. Après cette prédiction initiale, nous avons utilisé une fonction linéaire pour combiner les résultats du modèle avec le facteur de santé, dans le but de produire des recommandations équilibrant les préférences personnelles et les bénéfices nutritionnels. Atteindre cet équilibre s'est révélé être un défi important, car une attention excessive portée aux aspects de santé peut réduire la satisfaction des utilisateurs et l'efficacité globale du système.

Mots-clés : Système de recommandation alimentaire, Nutrition personnalisée, Alimentation saine, NeuMF, Apprentissage profond.

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List of Abbreviations

CB Content-Based Methods.

CF Collaborative Filtering.

FRS Food Recommendation System.

FSA Food Standards Agency.

FTO Fat Mass and Obesity-associated gene.

IMDB Internet Movie Database.

MAE Mean Absolute Error.

MF Matrix Factorization.

MSE Mean Square Error.

NCD Non-Communicable Diseases.

NDCG Normalized Discounted Cumulative Gain.

RMSE Root Mean Square Error.

RS Recommendation System.

SVD Singular Value Decomposition.

UN United Nations.

WALS Weighted Alternating Least Squares.

WHO World Health Organization.

General Introduction

A healthy diet is one of the essential foundations of human health and well-being. A balanced diet plays a key role in physical development, the regulation of physiological functions, and the prevention of chronic diseases such as cardiovascular diseases, obesity, and diabetes. However, in a world increasingly confronted with nutritional imbalances, whether related to deficiencies or excesses, malnutrition in all its forms represents a growing threat to food security and public health on a global scale [21].

In this context, guiding individuals toward more balanced food choices tailored to their personal needs becomes both an urgent and complex challenge. The digital revolution has profoundly transformed our lifestyles, including our relationship with food. Technology no longer merely supports our daily decisions; it actively influences our behaviors, down to simple actions like choosing a meal. Today, consumers no longer rely solely on their personal experience or traditional advice. They interact with a rich and constantly evolving digital environment, where nutritional information circulates abundantly through online platforms.

Social media occupies a central place in this dynamic by widely disseminating food-related content in the form of recipes, appetizing photos, or personal testimonials. This content shapes collective tastes and deeply influence eating behaviors. Nevertheless, this influence remains largely underestimated in discussions about the impact of technology on health. While the negative effects, such as eating disorders or advertising influence, are often emphasized, it is forgotten that these platforms can also serve as levers to encourage better eating habits.

When utilized effectively, these platforms could become powerful tools for positive change. Integrated into intelligent systems capable of understanding users' preferences and habits, they can promote personalized and relevant recommendations. This is where food recommendation systems come into play, aiming to help individuals make informed choices that align with their tastes and nutritional needs [34]. The more these recommendations are contextualized and adapted to the user's reality, the more likely they are to have a real impact on their eating behaviors.

In a world where fast and disorganized eating habits are often favored by busy lifestyles, the development of flexible and personalized recommendation systems becomes crucial. In recent years, significant advances have been made to design tools capable of anticipating users' food choices based on defined criteria.

However, despite these advances, current recommendation systems still present several important limitations. Many rely primarily on analyzing users' past ratings through techniques such as collaborative filtering. Yet, these approaches often neglect the intrinsic characteristics of foods, even though food preferences are frequently linked to specific ingredients that people wish to consume or avoid.

Another notable shortcoming is the insufficient integration of health considerations. Too many systems focus solely on user preferences without adequately taking nutritional guidelines into account, which can lead to unhealthy or even counterproductive choices for health.

Moreover, the role of user communities and food classifications is often underexploited, although they could significantly enrich behavior analysis and improve the relevance of recommendations. Finally, the lack of transparency in the logic behind recommendations constitutes a barrier to their adoption. Users are more inclined to follow a suggestion when they understand the reasons it is being proposed to them.

Despite these challenges, the question of personalizing food recommendations remains open. It raises complex issues related to the diversity of foods (ingredients, preparation methods, visual aspects), the variability of individual preferences, and the need to reconcile personal preferences with health recommendations.

This study aims to explore the scientific and technical foundations necessary for designing food recommendation systems. It places particular emphasis on the overall framework of these systems, the types of data used, the algorithms implemented, as well as the current challenges. The objective is to better understand how these tools can help guide individuals' food choices by taking into account both their personal preferences and health considerations. To achieve this objective, we are developing a hybrid food recommendation system based on the NeuMF (Neural Matrix Factorization) architecture [30]. This system relies on two strategies:

- The first involves integrating ingredients as well as a health factor directly into the NeuMF model.
- The second applies a health factor after the predictions are generated by NeuMF, by combining this factor with the predicted ratings in order to adjust the final recommendations.

This thesis is organized into four chapters as follows:

- **Chapter I** presents a review of recommender systems, introducing their fundamental concepts and the main methodologies used.
- **Chapter II** addresses the field of nutrition, emphasizing the importance of a balanced diet and the health consequences of poor nutrition. It then introduces Food Recommender Systems (FRS) as an intelligent solution to these challenges, outlining their basic concepts and approaches.
- **Chapter III** explores Food Recommender Systems based on Deep Learning. It provides an overview of deep learning and its relevance to recommender systems, through a review of existing works applying these techniques to FRS.
- **Chapter IV** is dedicated to the presentation and implementation of the NeuFM model in the context of food recommendation. This chapter details the approach and discusses the results obtained from the experiments and evaluations conducted.

Chapter I
Foundations of Recommender Systems

I.1 Introduction

Recommender Systems (RS) emerged as fundamental digital tools used to handle and manage the extensive online information available in the present-day world. These systems utilize user data insights to generate tailored suggestions which improve user navigation and purchase decisions. This chapter introduces RS fundamentals through definitions alongside their essential core concepts. It then moves into data and knowledge sources facilitating recommendation processes, types of recommendation techniques, and other approaches. It also examines how these systems evolved over time, how they work, along with their various roles and applications across different fields. Lastly, the chapter outlines the key challenges the recommendation systems presently confront.

I.2 Recommender System

Recommendation systems, or recommender systems as they are also called, they are a specific type of information filtering system that aims to predict the rating or preference a user would give to an item. In today's digital world they are everywhere and mandatory for e-commerce, streaming services, social networks and other services that have increasingly focused on personalization and user experience. Recommendation systems require several essential elements to operate properly. User profiles contain aggregated information about individual user interests along with their behavioral patterns and personal preferences obtained from previous interactions. Item profiles provide descriptions of their characteristics through attributes such as genre, category or features. Recommendation systems produce predictions about item ratings which serve as the foundation to suggest suitable items to users. The process of matching users to suitable items relies upon filtering methods including content-based filtering, collaborative filtering, and hybrid methods. These systems prioritize personalization as an essential goal since recommended items need to align with individual user preferences for maximizing engagement quality [1].

I.3 Data and Knowledge Sources

A Recommender system's data requirements align with the functions it serves within an information system framework. Systems generally gather information that includes items and users alongside user transactions. Standard RS models work with item ratings exclusively but modern advanced systems use information about user characteristics and transaction history data alongside item context.

There are three fundamental knowledge sources which include:

I.3.1 Items

These are the objects recommended by the system, varying from simple items like books and movies to more complex ones like jobs and financial investments. Each item is described by attributes that enhance recommendations, such as a movie's genre, director, and cast. An item's usefulness is determined by its positive value to the user, while irrelevant items may result in cognitive and monetary costs.

I.3.2 Users

RS aim to personalize recommendations by building user profiles. Simple profiles may only contain item ratings, whereas complex profiles integrate demographic information (age, gender, education), behavioral patterns (browsing history, past searches), and trust relationships between users, either explicitly defined or inferred from interactions.

I.3.3 Transactions

The system records user actions as transactions through logs which track fundamental information including item selections and recommended items and rating choices. Systems use different rating types for feedback which include numeric scale between 1-5, ordinal ratings, where users specify their level of satisfaction (e.g., “very satisfied,” “satisfied,” “dissatisfied”), or binary ratings, where users accept or reject the recommendation [2].

I.4 Types of Recommendation System

I.4.1 Non-Personalized Recommendation Systems

A non-personalized recommendation system offers product recommendations based on overall trends and popularity factors, rather than taking user behavior into account. It will more often recommend best-selling or trendy products with mass appeal. In doing so, it achieves good first impressions by surfacing content already popular among the masses at the expense of precision of personalized recommendations for mass appeal [3,4].

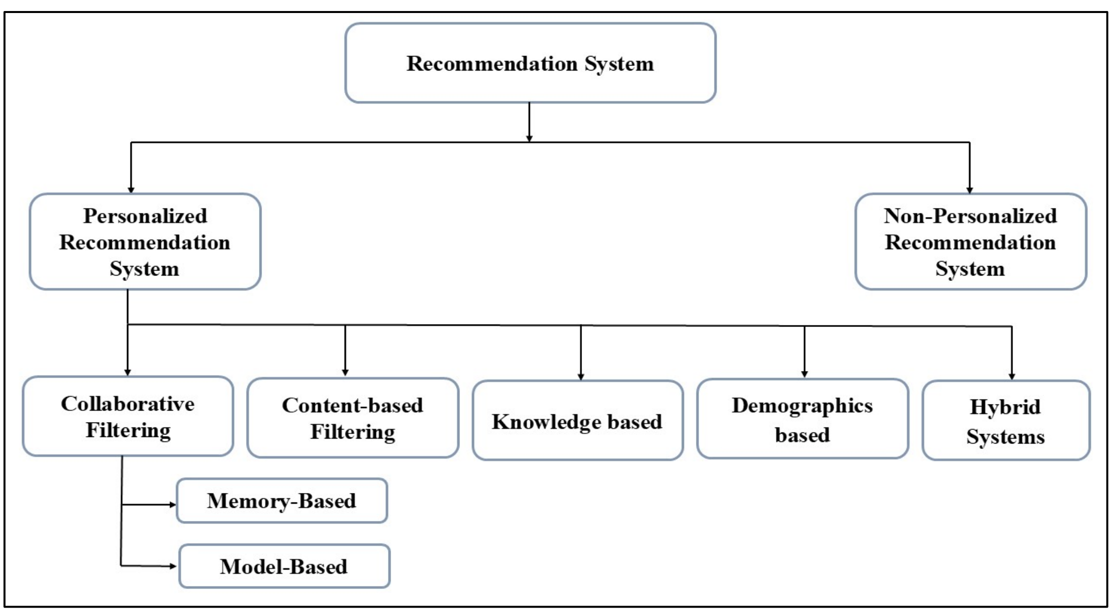


Figure I-1: Recommendation System Types.

I.4.2 Personalized Recommendation Systems

Personal recommendation systems work by taking into account user information like what the user has done before and what they like, along with demographic details. To forecast what products consumers could find interesting in the future based on their interaction with the past items such as ratings or purchases [3].

I.4.2.1 Content-based Filtering

Content-based filtering is a type of recommender system that makes suggestions according to a user's actions and interactions with items. It analyzes a user profile with the features and keywords related to items in a database, such as those in an online marketplace. This profile is created from the user's activities, which include purchases, ratings (likes and dislikes), searches, and clicks. These actions known as explicit feedback provide the baseline for the system's user ratings. Focus on individual needs leads to special recommendations and users are able to receive options that meet their description. With this, User A will see different suggestions than User B [5].

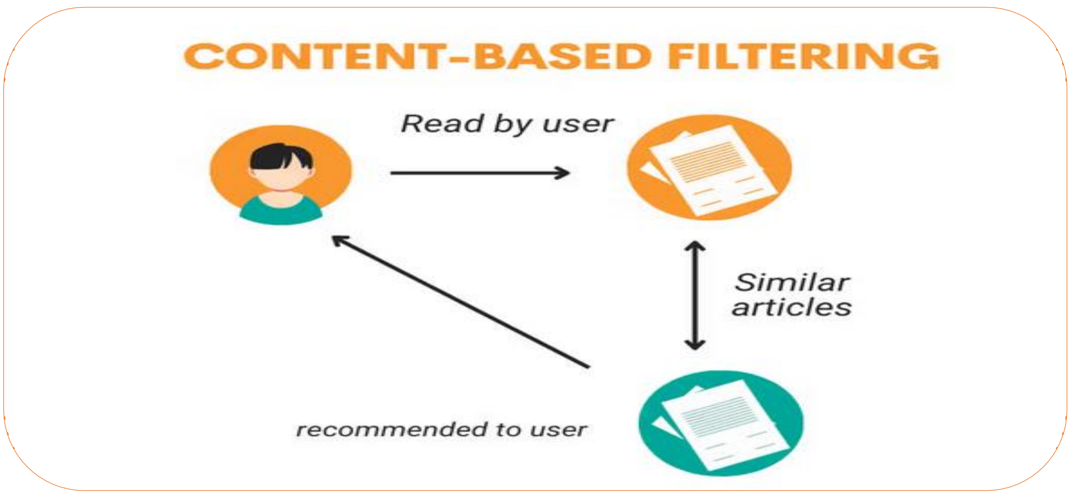


Figure I-2: Content-based Filtering [4].

- **Key components**
  - **a) User profile**

    Usually, a vector of features representing the users' preferences and tastes is used to visualize a user profile. The system looks for new items that might be appealing based on what a user has liked.
  - **b) Item profile**

    Each item in Content-Based Recommender requires a profile to be created which will serve as a representation of its key attributes. In a movie recommendation system, the features may include genre, director, year of release, cast, and even rating from IMDB.

c) Utility matrix

The utility matrix contains the user's preference of certain items. This matrix is used to identify the relationship between the user's preferred and disliked items in the data collected from the user. Each user-item pair in it is given a certain value, referred to as the degree of preference. Then, a matrix is drawn for a user with the relevant items to determine their preference relationship [6].

Table I-1: Utility Matrix of Movie Recommendation System.

Users/Movies	Movie1	Movie2	Movie3
User1	3		5
User2	5	4	2
User3	4	3	
User4		2	1

I.4.2.2 Collaborative Filtering

Collaborative Filtering is an approach to retrieve information that recommends products to users depending on the actions that other similarly behaving and similarly preferring users have taken towards a given item [7].

It can be further divided into:

1. Memory-based Collaborative Filtering

Memory-based CF is one method that uses the user's prior data based on ranking to determine how similar two users or items are. This method's primary goal is to characterize the degree of resemblance between users or objects and identify homogenous ratings to recommend the obscured items [8].

Memory-based CF includes two methods listed below:

- **User-based Collaborative Filtering**

This system generates recommendations through similarities between user preferences with other users. For instance, if two users rate similar movies highly, and one of them has watched and liked a movie the other has not, the system would recommend it, assuming they share similar tastes.

- **Item-based Collaborative Filtering**

The system suggests items which share characteristics similar to what the active user previously appreciated. For example, if a user enjoyed a particular dish like sushi, the system might suggest another type of Japanese cuisine [9].

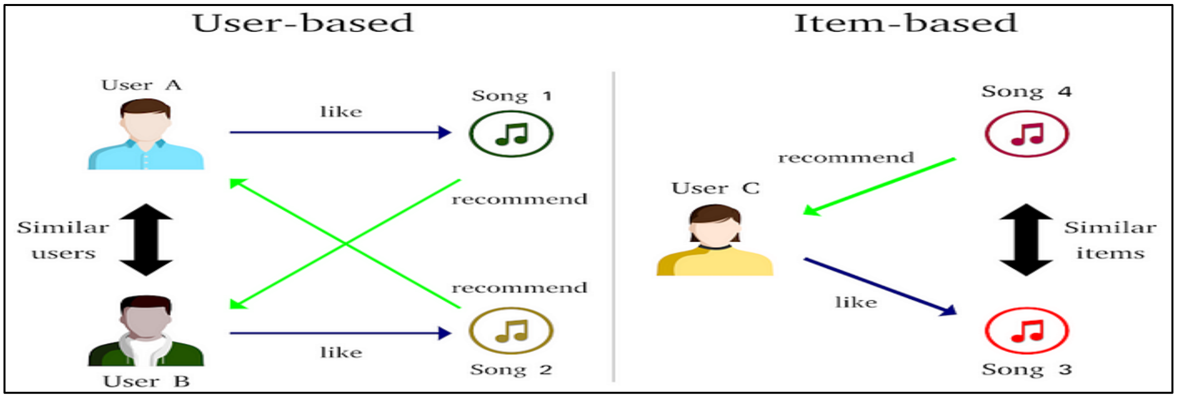


Figure I-3: Collaborative Filtering-based [11].

2. Model-based Collaborative Filtering

Model-based CF builds a predictive model from historical user–item interactions instead of calculating similarities between users or items directly. It extracts latent features that capture underlying user preferences and item characteristics using machine learning techniques like clustering deep learning and matrix factorization. These techniques enable scalable and precise recommendations without requiring the full user–item matrix to be stored in memory by effectively predicting missing ratings by reducing the dimensionality of the rating matrix [6,7].

- **Matrix factorization**

  Matrix factorization or matrix decomposition is a technique used to speed up the recommendation search process. The main idea of matrix factorization is to represent each user and each item as a matrix which is a decomposition of the original matrix. This type of reduction in dimensionality helps in solving the scalability problems posed by large matrices which are also very sparse. To obtain the original matrix, the matrices have to be multiplied together. This method of breaking down a sparse matrix into two condensed dense matrices of smaller sizes ensures that storage space is saved and speed of calculations is increased. These benefits are why matrix factorization is one of the most common methods used in collaborative filtering [10].

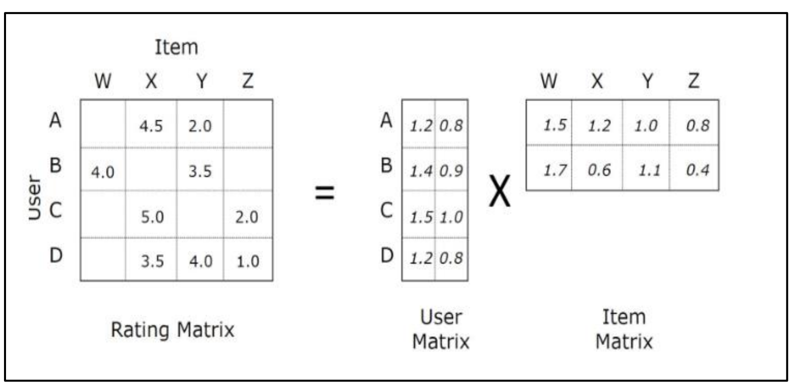


Figure I-4: Matrix factorization example.

- **Neural Matrix Factorization (NeuMF)**

Recently, deep learning has been recognized as an effective method for advancing recommender systems, particularly for modeling complex user–item interaction structures that traditional approaches fail to model effectively. An interesting recent implementation of this is Neural Matrix Factorization (NeuMF) proposed by He et al. [30], which expands classical collaborative filtering approaches by including both Generalized Matrix Factorization (GMF) and Multi-Layer Perceptron (MLP) within a shared neural architecture. GMF learns linear relationships through element-wise interactions of user and item embeddings, while MLP learns non-linear transformations through several hidden layers. NeuMF combines the two layers that allows it to learn shallow and deep representations and consequently improves the predictive power for recommendation over traditional matrix factorization techniques, which are limited to a simple inner product operation.

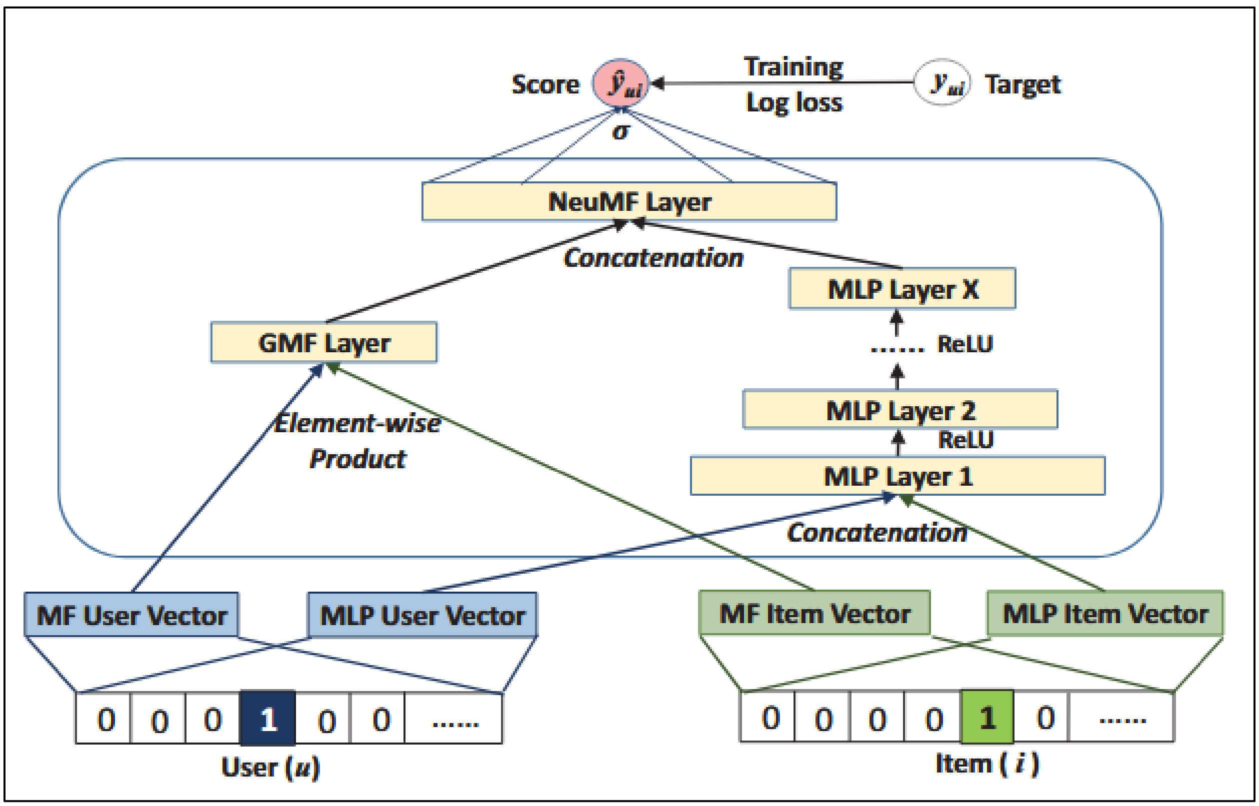


Figure I-5: NeuMF Architecture.

I.4.2.3 Demographics based

Demographic Recommendation Systems categorize users according to demographic characteristics to generate recommendations. This system uses user attributes like demographic data to provide recommendations based on age, gender, language, etc. The purpose of demographic RS is to address and resolve cold-start and scalability issues. The main benefit of demographic filtering RS is that, with just a few observations, they can produce results quickly and easily [12,13].

I.4.2.4 Knowledge based

A knowledge-based recommender system makes recommendations by utilizing available knowledge of users and products through predefined rules, constraints, or even case-based reasoning. To determine the best options, it takes into account particular user requirements rather than examining previous user interactions. They are useful particularly in decision-support applications because of their capacity to offer individualized and explicable recommendations [14,15].

I.4.2.5 Hybrid Systems

The hybrid filtering approach is combining multiple filtering techniques, it was developed to address common issues with the previously mentioned filtering techniques, including the cold start, overspecialization, and sparsity problems. Improving the precision and effectiveness of the recommendation process is another reason for implementing hybrid systems [16].

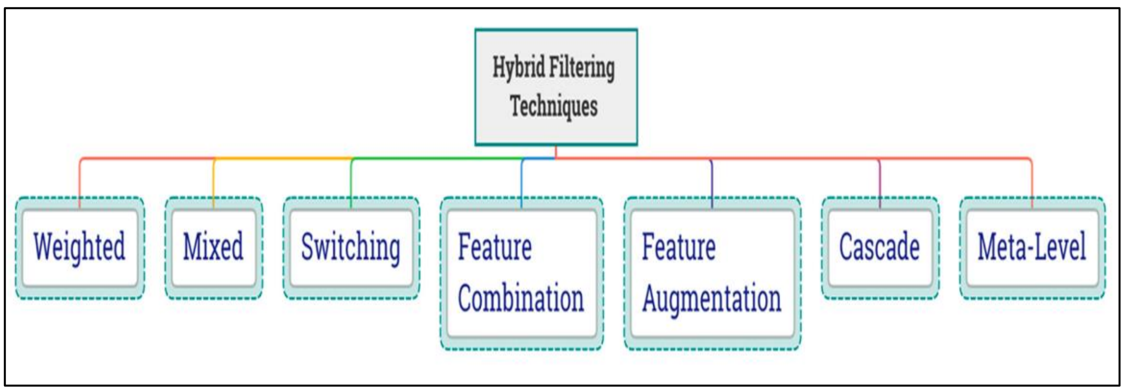


Figure I-6: Hybrid filtering strategies [12].

1. **Weighted**
   This technique computes scores for the suggested items by combining the output of multiple recommendation approaches. Every recommender is initially given the same weight which is modified according to the rating accuracy of users over time.
2. **Switching**
   One recommender is chosen from the components using a switching approach. A different system could be selected for a different user or profile. For instance, a different approach, such as the collaborative procedure, is tried if the content-based strategy is

unable to provide a recommendation that is accurate with high confidence. This approach does not prevent every issue that RSs face, such as the ramp-up difficulty. This hybridization approach makes the assumption that a trustworthy criterion exists for which the choice to switch should be made. The remaining unselected elements no longer play a part in the left suggestion process when the switching decision is made.

3. **Mixed**

   In this strategy offers recommendations from various systems presented alongside each other, making it advantageous when multiple suggestions are required simultaneously. It does not merge results, which can complicate the integration of separate lists. Techniques for combining these may depend on anticipated ratings or the confidence level associated with each recommender.

4. **Feature Combination**

   This approach merges complementary features from one recommendation method into another. For instance, collaborative features can enhance content-based systems by incorporating collaborative information as supplementary data. This reduces the dependence on user ratings while still taking aggregated data into account.

5. **Cascade**

   The cascade method creates a hierarchical framework where more effective techniques are prioritized over less effective ones. Lower-priority recommenders may assist in resolving ties without undermining the decisions made by higher-priority systems. This approach is resilient to interference from less reliable techniques, as it focuses on refining suggestions rather than contradicting earlier recommendations.

6. **Feature Augmentation**

   This technique produces ratings for items and incorporates this information into subsequent recommendation processes. It is especially beneficial for enhancing a well-established primary recommendation component with additional data sources. Unlike the cascade method, the outputs from the initial recommender are directly utilized in the next stage.

7. **Meta-Level**

   This strategy involves using a model created by one recommender serves as the input for another. This differs from feature augmentation in that it utilizes the entire learned model rather than just its features. Implementing this method can be complex, as not all recommendation techniques can generate a usable model. However, it effectively condenses representations of user preferences, facilitating easier subsequent analysis [12].

I.4.3 Other Approaches

I.4.3.1 Context Awareness Recommendation Systems

Context-aware recommendation methods elevate standard recommendation systems by incorporating situational aspects from time to location and social settings. The evolution shifts rating computations from simple (User × Item → Rating) format to multi-dimensional (User × Item × Context → Rating) structure which incorporates extra contextual elements. There are three fundamental approaches to incorporate context within recommender systems. Recommender systems employ contextual pre-filtering as a method to narrow down data selection next to recommendation generation. Contextual post-filtering operates after the initial recommendations get generated by applying context for result refinement and re ranking. Contextual modeling includes context as a direct component of its recommendation algorithm which affects model predictions through the development process. The combination of these approaches allows recommendation systems to use contextual information effectively thus generating more personalized and accurate suggestions [17].

I.4.3.2 Social Network-based Recommendation Systems

Social network-based recommendation relies on the relationships and interactions between users to provide personalized and relevant suggestions. By analyzing the structure of the social network as a graph, it enables the prediction of new links (link prediction), the recommendation of people to follow, professional partners, or social brokers who connect different communities. This approach, which explicitly integrates social connections, enhances the quality of recommendations compared to traditional methods by taking the social context into account. As a result, it facilitates the creation of new connections, strengthens community cohesion, and promotes collaboration in various social and professional environments [17].

I.4.3.3 Community-based Recommendation Systems

Community-based recommender systems utilize implicit or explicit social groupings to generate suggestions. The core idea is that users tend to trust recommendations coming from their community or social group. With the rise of Web-Based Social Networks (WBSNs), these systems often considered a subset of social recommender systems, have gained increased attention. Communities can be inferred from factors such as interaction frequency (e.g., shared activity or communication) or network-based clustering methods that identify groups with shared interests [2].

I.5 Evolution and Functionality of Recommender Systems

Recommender systems (RS) emerged during the early 1990s by addressing personal email and information filtering requirements. The first major achievement in recommender systems came when Tapestry and GroupLens implemented collaborative filtering to deliver personalized recommendations based on user feedback. RS demonstrated increased usage following the Web's expansion particularly within e-commerce where Amazon implemented extensive recommendation systems. Research progressed to matrix factorization and machine learning algorithms after the Netflix Prize motivated better approaches for rating prediction. RS development progressed from basic algorithmic optimization to focus on recommendation diversity and novelty. The past decade has witnessed an increase of research on deep learning and hybrid modeling techniques that incorporate social network and user context data to enhance recommendation outputs. RS continues to face several significant issues related to human-computer interaction together with determining its effect on how users behave [18]. Building on this evolution, it is essential to understand how recommender systems operate today.

The functioning of RS follows a structured process involving several key steps:

1. **Data Collection:** Data plays a crucial role in the functioning of recommendation systems. Insights are extracted from key aspects of an individual's online behavior, previous purchases, and personal attributes. The effectiveness of a recommendation engine in providing relevant suggestions increases with the volume of data it can access. Data can be categorized into two primary types. The first type is implicit data, which includes information about the users search history clicks purchases and other interactions, it is collected by a company each time a user visits their site. Explicit data is the second category includes user-generated content like reviews ratings and comments. In order to identify users with comparable profiles recommendation engines also use demographic information such as age gender and general interests. Compiling a large amount of customer data is necessary to build an effective recommendation engine [19].
2. **Data Storage:** After gathering user data, it must be stored correctly, depending on the type and volume of the data. Companies keep records not just of users but also of what they sell, whether they are shoes, books, or streaming media like movies and shows. Information about these items includes price, category, genre, or brand. These details are used by recommendation systems to understand product relationships and match them with user preferences accurately. Together, user data and item data are essential for creating personalized suggestions [19].
3. **Data Analysis:** A machine learning system is applied to the data for exploration and analysis. While recommendation engines employ a variety of algorithms to analyze data singular value decomposition (SVD) is the most widely used. Using this mathematical method a matrix is divided into three smaller matrices in an attempt to identify patterns and relationships in the data and assess how strong those relationships are. The objective is to gain a deeper comprehension of a large data sets underlying structure in order to extract valuable information [19].
4. **Filtering and Recommending:** Recommendation engines apply various mathematical formulas and rules on analyzed user and item data to filter out the most pertinent options which vary based on the type of recommendation system used. Then on websites, in mobile apps, or in emails these filtered recommendations appear as "You might like" or "Recommended for you". They attempt to provide timely, personalized

content that is individualized to that particular user. As users interact with these suggestions, the system learns and evolves, creating a feedback cycle that tailors future recommendations and ensures continuity across devices and services [19].

I.6 Recommender System Roles and Application

Recommender systems (RS) play a dual role, serving both the service provider and the user. The initial purpose of these systems appeared to enhance user discovery but research shows they support vendors in their objectives involving increased sales numerous item selection better user perceptions larger client retention stronger understanding of consumer choice preferences. RS enhance user experiences by recommending relevant items and personalized content based on context while also providing bundled recommendations such as packaged travel offerings. They also allow users to browse catalogs more easily, test the system's reliability, improve their profiles for better future recommendations, express themselves through feedback, help other users by sharing experiences, and in some cases, influence the decisions of others. Ultimately, a successful RS must balance these two perspectives to create value for both sides [2].

Beyond their general roles, recommender systems have been applied across a variety of domains including e-government to personalize services for citizens and businesses, often using hybrid techniques combining collaborative filtering, content-based filtering, and knowledge-based approaches. In e-business, they enhance online shopping experiences for consumers and facilitate business-to-business interactions like partner selection and product catalog management, frequently integrating knowledge-based methods. E-learning platforms employ recommender systems to suggest suitable courses and learning materials, leveraging data mining, pedagogical rules, and social network analysis. Similarly, e-libraries utilize hybrid collaborative and content-based filtering to help users discover resources [17].

I.7 Challenges in Recommendation Systems

1. **Cold start** problem occurs when a recommendation system lacks sufficient data to generate precise recommendation. It is like a car engine failing to start when the car is cold. Cold start comes in two varieties. The first is product cold start in which no user interaction data is available for a new product when it is added to the platform. The second kind is user cold start in which no information about a new users' preferences or interactions is available when they sign up for the platform. Techniques like the Bayesian classifier and projection in WALS (Weighted Alternating Least Squares) are used by recommendation systems to address this problem.
2. **Data Sparsity** is a frequent issue in recommendation systems because users often rate only a small number of items. This leads to a user-item matrix, where up to 99% of the ratings are missing. To address this problem, recommender systems use strategies such as: Modeling the preferences of users based on their behaviors and trusted social friends, using trust to improve the stability of recommender systems, the merge strategy, which involves the inclusion of the trusted neighbors of the active user to improve prediction accuracy.

3. **Scalability** is the difficulty of sustaining performance in recommendation systems as the number of users and items increases quickly. Because algorithms need to be able to find useful recommendations in real time from massive datasets. Techniques for avoiding this are dimensionality reduction like SVD and clustering that reduce computation by simplifying data and grouping similar users together.
4. **Diversity** is about offering different types of recommendations, not just those similar to what someone already enjoys. If we only suggest similar items, people might not discover special or unique things they could like. We measure diversity by how surprising or unexpected the recommendations are ("surprisal") and how unique they are for each person ("personalization"). Mitigation is achieved by balancing diversity and accuracy. Techniques like re-ranking based on dissimilarity or penalizing highly similar items in the top-N list can help broaden the range of suggestions and promote more diverse recommendations [12].

I.8 Evaluation Metrics in Recommendation Systems

Evaluation metrics are essential for assessing the effectiveness of recommendation systems. They provide insights into various aspects of system performance, helping to improve user engagement and satisfaction [20].

I.8.1 Similarity Metrics

These metrics quantify how closely items or user preferences align. Some key similarity metrics include:

- **Cosine Similarity** calculates the angle between two vectors through their cosine value to determine their orientation correspondences. Text-based and attribute-rich data functions best with this measure because it evaluates patterns instead of absolute values to determine user preferences.

$$\cos\theta = \frac{A \cdot B}{\|A\|\|B\|}$$

  - $A \cdot B$: dot product of vectors A and B.
  - $\|A\|\|B\|$: magnitudes (lengths) of vectors A and B.
- **Euclidean Distance** is used in evaluating recommendation systems when comparing profiles in a feature space with numerical attributes to gauge similarity based on the 'straight-line' distance between points (user-item pairs).

$$d(A,B) = \sqrt{\sum_{i=1}^{n}(A_i - B_i)^2}$$

  - $(A_i - B_i)^2$: squared difference between each corresponding dimension.

- **Jaccard Index** is used to assess how similar two sets are by comparing the size of their intersection to the size of their union.

$$J(A,B) = \frac{(A \cap B)}{(A \cup B)}$$

  - (A∩B) represents the number of elements common to both sets, while (A∪B) is the total number of distinct elements present in either set.
- **Pearson Correlation Coefficient** assesses the linear correlation between two variables.

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

  - X_i, Y_i: values in vectors X and Y.
  - $\bar{X}, \bar{Y}$: means of X and Y, respectively.
- **Manhattan Distance** computes the distance between two points by summing the absolute differences of their coordinates.

$$D_{Manhattan}(A,B) = \sum_{i=1}^{n}|A_i - B_i|$$

  - $|A_i - B_i|$: absolute difference between vectors A and B at dimension i.

I.8.2 Predictive Metrics

These metrics are concerned with the accuracy of predicting user preferences, which involves:

- **Root Mean Square Error (RMSE)** represents the square root of the average of the squares of the differences between predicted and observed value.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

  - where N is the number of observations, $y_i$is the actual value of an observation, and $\hat{y}_i$ is the predicted value.

- **Mean Absolute Error (MAE)** evaluates the average absolute differences between predicted and actual ratings.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

- **R^2** measures how much of the variability in the dependent variable can be explained by the independent variables.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Where:

- SS_{res}=$\sum(y_i - \hat{y}_i)^2$ is the residual sum of squares (error between predicted and actual values).
- SS_{tot}=$(y_i - \bar{y}_i)^2$is the total sum of squares (variance of the actual values from their mean).
- y_i is the actual value.
- $\hat{y}_i$ is the predicted value.
- $\bar{y}_i$ is the mean of the actual values.

I.9 Conclusion

In conclusion, this chapter emphasized the value of recommendation systems in digital information management by offering tailored recommendations. It described Recommender Systems, explaining its definition, key concepts, data and knowledge sources such as items, users and transactions, it also studied the various types of recommendation systems. Furthermore, it explored the evolution and functioning of RS, emphasizing the systems' roles and applications in different areas. It finally discussed the main challenges of these systems. These foundations provide essential knowledge needed for building effective and reliable recommendation systems that work most successfully in areas like healthy food promotion.

Chapter II
Food Recommendation System

II.1 Introduction

This chapter examines the relationship between nutrition, health, and technology in today’s complex food landscape. It highlights the importance of balanced nutrition, its role in disease prevention, and the challenges individuals face in maintaining healthy diets. The discussion then shifts to emerging food recommendation systems as potential solutions, analyzing the factors that influence food choices and how these can be modeled effectively. It also includes a critical analysis of existing systems and evaluates their impact on public health, particularly in promoting healthier eating habits, reducing diet-related diseases, and enhancing overall well-being, while acknowledging the current limitations and challenges these systems face.

II.2 Importance of Balanced Nutrition

The balanced nutrition is a diet containing all the elements that provide the body with the level of energy and health it needs, and it is enough to enable the body to perform the various functions necessary to maintain life. This involves consuming macanutrients such as carbohydrates, fats, and protein, and certain micronutrients like vitamins and minerals [21].

II.2.1 Macronutrients

- **Carbohydrates:** can be divided into two types, simple carbohydrates (fast sugars) and complex carbohydrates (slow sugars). These nutrients supply the body with its major source of energy and fueling brain function. In order to avoid blood sugar levels increasing at a rapid rate while sustaining energy, the complex varieties are preferred. Simple carbs can be found in greater amounts in sweet foods (candy, cakes), soda, juices, natural sources like fruits and dairy products and the complex category can be obtained from whole grains (brown rice, whole wheat bread, oats), legumes (beans, lentils) and starchy vegetables (potatoes, corn) [22].

- **Proteins:** are the fundamentals elements for the construction and the repairing of body tissues (muscles, skin, hair). These nutrients serve in increasing the enzymes, hormones, and antibodies that boost immune functions. The body needs essential amino acids which are not produced by the body hence obtained by a variety of protein such as lean meat, fish, eggs, dairy products, legumes, and nuts [23].

- **Fats:** considered as crucial source of energy, and play important role in hormone production, support the absorption of fat-soluble vitamins and maintain both brain health and organ protection. They are categorized into healthy fats (unsaturated fats) found in olive oil, nuts, seed, and fish (omega-3, 6), plus unhealthy fats (saturated and industrial trans fats) that should be restricted due to cardiovascular risks [22].

II.2.2 Micronutrients

- **Vitamins:** are organic molecules that human body cannot produce in sufficient quantities therefore they must be obtained through food. They are divided into types:

1. **Water Soluble Vitamins (vitamins C and B):** need daily consumption because they dissolve in water and are rapidly eliminated in excess. They found in fruits vegetables and cereals.
2. **Fat soluble vitamins (A, D, E, and K):** dissolve in fat before being stored in the body yet excessive intake becomes harmful, so these vitamins exist mainly in oils dairy products and egg yolks.

- **Minerals:** inorganic elements that the body requires for numerous various functions like bone construction, nerve transmission, muscle contraction, and fluid balance. They can be categorized into: Macrominerals which are required in large amounts (calcium, potassium, magnesium), and Trace minerals which are required in smaller amounts (iron, zinc, fluoride) [24].

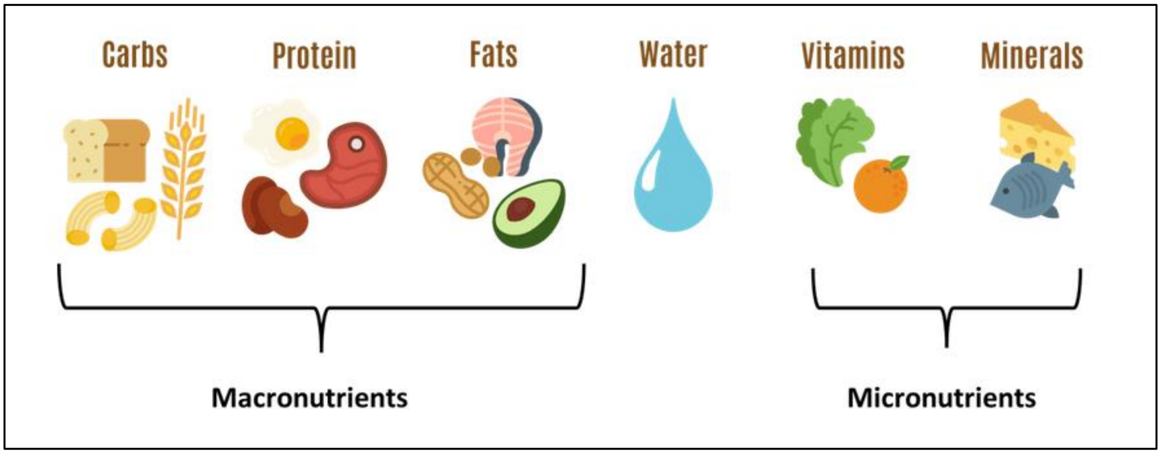


Figure II-1: Macronutrients and Micronutrients Examples [23].

II.2.3 Health benefits of balanced nutrition

- **Immune System Support**: Adequate nutrition plays an essential role in enhancing immune activities through its delivery of crucial vitamins and minerals which fight diseases and infections.
- **Mental Health**: Emotional well-being, focus memory, brain development and brain function, are all enhanced by a balanced diet which also lowers anxiety and depression levels.
- **Growth and Development**: Nutrition is a key to maintaining physical growth, assisting in mind development, as well as enhancing strong bones, muscles, and organs.
- **Weight Management**: Nutritious diet ensures healthy weight by providing the body with the right quantity of calories and nutrients where the possibility of excessive or insufficient weight gain is minimal.

- **Improved Digestion and Gut Health**: Conscious balanced food consumption equally promotes health digestion by enhancing the frequency of bowel movements and maintaining proper balance of gut microbiota which is important for digestion [21,25].

II.2.4 Role in disease prevention

Since a balanced diet takes into account a number of health factors it is crucial for preventing illness. By prioritizing whole food, minimally processed foods, saturated fats and added sugars, proper nutrition significantly lowers the risk of chronic diseases like cancer diabetes and heart disease. A diet of whole grains, legumes, fruits, vegetables, nuts, seeds, and omega-3 fatty acids may decrease inflammation and cardiovascular function. Avoiding refined carbohydrates and eating a diet high in fiber can help control blood sugar and insulin sensitivity. Phytochemical-dense foods such as cruciferous vegetables and berries can decrease cancer risk by fighting oxidative stress. In addition, a healthy diet helps prevent diseases like osteoporosis, and Alzheimer's, enhances cognitive function and supports bone health by guaranteeing adequate intake of calcium and vitamin D. Although dietary modifications can aid in the prevention of chronic illnesses its crucial to keep in mind that nutrition should be used in support of not in place of knowledgeable medical advice and care [26,27].

II.3 Challenges in achieving balanced nutrition

- **Time Constraints**: Many people face difficulty in finding time for planning meals, shopping, and cooking. The demands of modern life usually lead towards the consumption of fast food or prepared meals, which are usually less nutritious.
- **Diet Confusion**: There's a lot of mixed information about diets that can be confusing. With so many fad diets and differing nutritional advice, understanding what truly makes up a healthy diet can be difficult.
- **Cultural Influences**: Cultural preferences and traditions around food can impact dietary choices. Some cultural diets may not align with current nutritional guidelines, making it challenging for individuals to adopt healthier eating patterns without feeling disconnected from their heritage.
- **Unsupportive Social Environments**: An unsupportive home or community environment can make it harder for individuals to stick to healthy eating plans. Support from family and friends is crucial for maintaining motivation and accountability.
- **Economic Barriers**: Healthy foods are often more expensive than processed alternatives, creating a financial barrier for many families. Economic constraints can lead individuals to prioritize cost over nutritional value [28,29].

II.4 Consequences of Poor Eating Habit

Poor nutrition occurs when the body is unable to obtain the proper essential nutrients for normal functioning. It often results from an unbalanced diet, which may be the result of insufficient consumption of nutrient-rich foods, excessive intake of unhealthy foods with high saturated fats, added sugar, or salt, or over-eating and under-eating. Malnutrition affects physical appearance, health, and mental processes, as well as behavior and mental health, highlighting its significant contribution to maintaining bodily function [31].

II.4.1 Physical Health Consequences

- **Obesity and weight gain:** overconsumption of processed foods and sugars lead to being overweight; the risk for diabetes, high blood pressure, and certain types of cancer also increases.
- **Nutritional deficiencies:** Lacking necessary nutrients causes immediate medical issues, including anemia which results from iron deficiency and weak bones due to insufficient vitamin D and calcium, and immune system compromise. For children, it might cause stunted growth and developmental problems.
- **Increased risk of chronic diseases:** Frequent consumption of foods that have saturated fats, cholesterol, and sodium raises the risk of long-term disease like heart disease, stroke, and certain cancers.

II.4.2 Mental Health Consequences

- **Mood disorders:** High-sugar and processed foods lead to depression and anxiety, while a healthy diet improves mood and reduces fatigue.
- **Cognitive decline:** Because nutrients are essential for the health and function of the brain chronically poor eating can cause memory loss and raise the risk of dementia.

These negative effects of bad eating habits really emphasize how important it is to raise awareness and educate people about nutrition. By encouraging a balanced diet and cutting back on unhealthy foods, can significantly enhance overall health and prevent avoidable complications [32].

II.5 Current public health goals and nutritional recommendation

Promotion of healthy food consumption has become a priority on the global agenda in the fight against malnutrition. Eliminate food insecurity and improve overall well-being Basic public health goals and recommendations include:

1. **Sustainable Healthy Diets**: It’s important to maintain a diet that provides the right nutrients while causing minimal harm to the environment. These foods need to be affordable, easily accessible, and suitable for different cultural needs. This concept is a major focus in the 2024 World Food Policy Report [33], which calls for changes in food systems to ensure everyone has fair access to nutritious food.

2. **Reduction of Malnutrition and Non-Communicable Diseases (NCDs)**: Tackling the double burden of malnutrition including undernutrition and obesity, requires public health interventions to address nutrient deficiencies and prevent diet-related diseases. Poor-quality diets are cited as the leading cause of disease globally.

3. **Focus on Micronutrients**: Prevention of micronutrient deficiencies such as calcium, potassium, vitamin D and iron, especially among the vulnerable, is still a priority. Over 2 billion people cannot afford to buy a healthy food [33]. It has a major impact on their nutrition status.
4. **Improving Food Environments**: Solutions include improving availability and affordability of healthy options and reacting to consumer demand and policy responses to reduce unhealthy food consumption.
5. **Alignment with Global Goals:** Aligning the efforts with UN Sustainable Development Goal2 (Zero Hunger) for the eradication of hunger and all forms of malnutrition by 2030. Public health research and policy are aimed at transforming the food systems in such a manner so that these objectives can be fulfilled effectively [33].

II.6 The raise of Food Recommendation Systems

In today's era, the food available has become very complicated with a myriad of factors including globalization, commonality in the prevalence of food trends, and an information explosion online. Customers encounter an unlimited menu between fast foods and organic foods without being able to identify suitable dietary choices. The abundance of information confuses customers while leading them to choose unhealthy foods that negatively affects their health outcomes. Thus, there is an increased need for personalized food recommendation systems that will lead individuals to healthier diets based on their personal tastes, nutritional needs, and health goals. These systems assist users with understanding food variety by offering customized suggestions that match their tastes and health requirements as well as their selected lifestyle options [34].

II.6.1 Food recommendation system

Food recommendation system (FRS) is particular type of recommended systems that handle vast amounts of data with the aim of suggesting personalized meals or recipes, considering user preferences, dietary limitations, and food ingredient compatibilities. These systems are relevant in enabling healthy eating habits in healthcare and prevention of diseases like diabetes and heart conditions by enabling users to track their nutritional intake. As an effective tool in today's diversified food environment, FRS enables users to find new meal options according to their health issues and nutritional goals, thereby enabling individuals to manage nutrition and well-being more effectively [35].

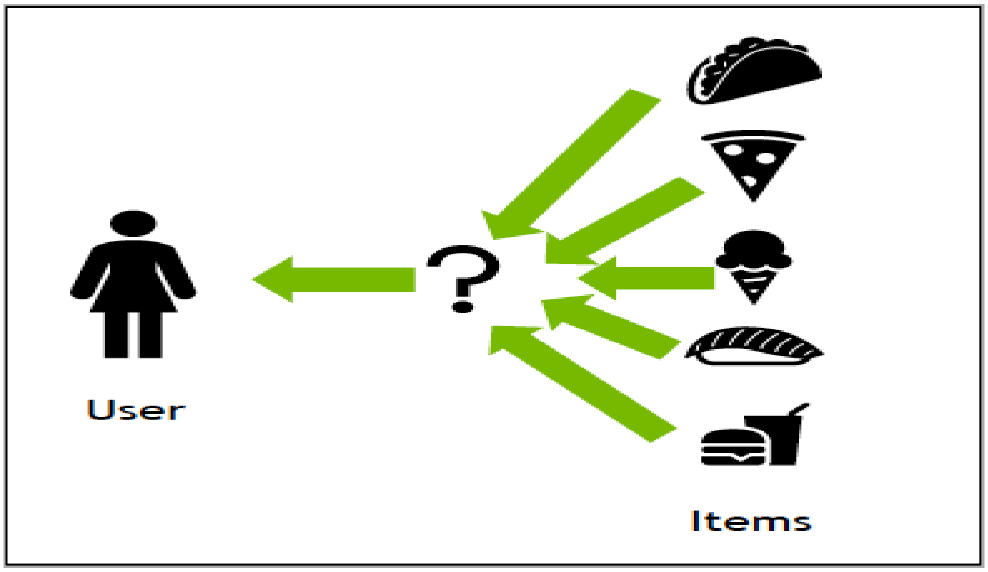


Figure II-2: Food Recommendation System [36].

II.6.2 Types of Food Recommendation system

1. Content-Based Methods (CB)

Content-based recommendation methods aim to match users' individual preferences with recipe features by analyzing the content of items, such as ingredients. Freyne and Berkovsky [37] proposed a method that breaks down recipes into individual ingredients and scores them based on how frequently they appear in recipes the user has rated positively. For example, if a user enjoys recipes containing tomatoes, the system recommends other recipes with the same ingredient. This approach is effective in capturing user taste profiles but tends to overfit to known preferences, limiting novelty and diversity in the recommendations. To address such limitations, Teng et al. [38] introduced the use of complement and substitution networks. Complement networks identify ingredients that commonly co-occur in recipes, while substitution networks are built from user-generated suggestions for replacing ingredients. Their experiments demonstrated that incorporating these relational ingredient networks improves the accuracy of preference predictions compared to more traditional feature-based approaches. However, these methods depend heavily on the availability and quality of user interaction data, and the construction of such networks can be computationally demanding.

2. Collaborative Filtering-Based (CF)

The main goal of this approach is to recommend foods based on user preferences that match. It makes use of the notion that people with comparable ratings typically have comparable tastes. For instance, in order to identify users with similar preferences, the authors [37] investigated a nearest neighbor approach that used Pearson correlation on user ratings however this method did not perform as well as their content-based method. Other work, such as Harvey et al. [39], showed that Singular Value Decomposition (SVD) performed better than both their content-based and earlier collaborative filtering techniques.

3. Hybrid Methods

To improve the precision and applicability of recommendations hybrid recommenders combine several recommendation techniques. In order to improve recipe suggestions researchers have proposed a number of hybrid approaches such as the work presented in [37] who combined content-based methods that leverage both ingredient features and user behavior with user-based collaborative filtering. In subsequent work, they introduced a hybrid model that merged three different recommendation strategies using a switching method that adjusts based on the ratio of items rated by a user to the total number of items available. Additionally, the work presented in [39] achieved improved performance by combining SVD with user and item biases.

4. Context-Aware Approaches

Context has a significant role in food recommendations, with user preferences being influenced by gender, time, hobbies, location, and food availability. Studies have explored how recipes are rated, bookmarked, or shared using simple filtering algorithms. The study in [40] found that user ratings are affected by factors such as ingredient availability, nutritional properties, preparation clarity, and day of the week. However, a clear understanding of which background factors are most crucial and how to incorporate them algorithmically is still lacking.

5. Group-Based Methods

Group-based food recommender systems address scenarios where people make food choices together, such as with family, friends, or colleagues. Individual food choices are greatly influenced by the presence of others, their tastes and the reasons they congregate according to social psychology. Group recommender systems take this into account by producing a list of foods that are appropriate for the group as a whole rather than just for a single person Although research in this area is limited, early work in this domain [37] explored various strategies for recommending recipes to groups, finding that personalized methods perform best, though not feasible for all users. More recent work by Elahi et al. [41] introduced a mobile system that uses tags, group roles, and a designated group leader to generate meal suggestions based on a group utility score that aggregates preferences from all group members.

6. Health-Aware Methods

Integrating nutrition and health into the recommendation process is a growing area of research in food recommender systems. This is driven by the desire to solve health issues and enhance the nutritional intake of the users. For example, Elsweiler et al. [42] proposed the combination of user reviews and a nutritional error score in order to balance taste and healthiness. Ge et al. [43] proposed a calorie balance function that adjusts recommendations based on the difference between a user’s caloric need and the calories of a recipe, while Trattner and Elsweiler [44] incorporated health scores from the WHO and FSA during the post-filtering stage. Nutritional quality enhancement, however, compromises accuracy, and existing methods continue to struggle with special diets. Novel solutions, such as ingredient substitution and constraint-based planning, show potential but require ongoing development.

II.6.3 Factors Influencing Food Choices

Food choices are driven by a mix of biological needs, personal preferences, social influences, economic factors, and environmental conditions. These elements interact to shape individual eating habits and dietary behaviors.

II.6.3.1 Key Dimensions Influencing Food Choices

The selection of foods depends on multiple interactions between biological needs, economic constraints, social contexts, psychological factors, and environmental conditions. The basic biological needs involving hunger and taste preferences and sensory satisfaction act as primary drivers of food choices while economic limitations such as cost and accessibility determine practical food choices. The combination of societal conventions with family traditions and the impact friends have on dietary choices establishes eating patterns which tend to remain consistent. Individual psychological aspects including stress and mood swings and cravings can induce emotional or impulsive eating behaviors. People’s food attitudes are influenced by their educational background and media exposure as well as their nutritional knowledge yet barriers like poor cooking skills combined with scheduling constraints and expense perceptions prevent them from making healthy meal choices. Sustainable dietary changes require interventions that recognize multiple factors through tailored approaches which respond to specific circumstances [45].

II.6.3.2 Modeling Preferences for Recommendation

Building food recommendation models requires detailed user and food item representations through methodologies like ontologies and semantic networks. User profiles emerge from data obtained through questionnaires together with behavioral records and health data which document individual food requirements and food choices along with dietary limitations. The characterization of foods takes place through ontologies which establish categories and define ingredients and nutritional values together with preparation methods to create a systematic interpretation of food features. User trust and satisfaction improve in recommender systems by applying the Food Explanation Ontology (FEO) and semantic modeling for joining food characteristics to user profiles resulting in transparent recommendations [46].

II.6.4 Critical Analysis of Existing Systems

Food Recommendation Systems serve as essential tools that help users find meals suitable for their dietary standards and individual taste preferences. The recommendation methods content-based and collaborative filtering power these systems to offer personalized service while managing information overload. FRS systems that integrate nutritional data facilitate users to choose healthier food options while relying on user feedback to evolve their recommendations. Advanced systems combine contextual information such as time and location data with human-like conversational interfaces to address specific health requirements. However, several current FRS solutions come with various key restrictions. Many systems utilize only basic user attributes to generate recommendations so their personalization capabilities remain limited. The performance of recommendation systems deteriorates due to data limitations and sparse data while the lack of evaluation standards makes it difficult to properly compare system performances. Many recommendation systems demonstrate cultural regional biases through their preference for specific cuisines while at the same time they underutilize visual information despite its importance for food selection. The lack of predefined future development paths and public research benchmarks in few systems impedes systematic solutions for known shortcomings [34].

II.6.5 Impact and Benefits of Personalized Recommendations

This section explores how personalized food recommendations encourage healthier habits, reduce diet-related diseases, improve quality of life, and support large-scale public health through tailored, effective dietary guidance.

II.6.5.1 Encouraging Healthier Eating Habits

- **Personalized Motivation:** Research indicates that when compared to generic dietary recommendations personalized recommendations can boost motivation and adherence to healthier eating practices. The reason for this is that customized suggestions are made based on each person's tastes, way of life and health objectives.
- **Improved Dietary Quality:** By decreasing consumption of discretionary foods and increasing consumption of nutrient-dense foods personalized nutrition programs frequently result in higher-quality diets.
- **Behavioral Change Techniques:** Personalized nutrition employs behavioral change techniques, like goal setting, self-monitoring, and motivational interviewing, which are effective at establishing healthier eating patterns.
- **Increased Food Literacy:** Making educated food choices is encouraged when people receive personalized insights that help them comprehend food labels nutrient content and portion control.
- **Cultural and Preference Alignment:** Higher compliance rates and longer-lasting dietary changes are the outcome of recommendations that take individual taste preferences and cultural food customs into account [47,48].

II.6.5.2 Reducing the Prevalence of Diet-Related Diseases

The major goal of personalized, nutrition is to reduce the prevalence of diet related diseases through the customization of dietary therapy to an individual's genetic, phenotypic and lifestyle features. This personalized approach has been shown to effectively prevent and manage Obesity, diabetes cardiovascular disease and cancer. Personalized nutrition improves health outcomes like gut health and cholesterol status by addressing individual nutrient deficiencies, food sensitivities, and metabolic variability [49]. Because personalized advice contains dietary advice based on the individual’s goals, preferences, and health status, it improves compliance with healthier diets which has been associated with improved long-term outcomes [50]. Furthermore, diet interventions such as the DASH and Mediterranean diets, have been found to be optimized to effectively treat hypertension, enhance cardiovascular well-being, and prevent cognitive decline [51]. Personal nutrition similarly answers the individual health needs as well as the larger public health epidemic by integrating genetic and behavior data to develop a sustainable approach to decreasing the disease burden linked with diet.

II.6.5.3 Population-Level Health Improvements

Promoting population-level health requires scalable and easily accessible personalized dietary recommendations via digital platforms which enable broad dissemination beyond particular clinical settings. For example, web-based interventions have demonstrated great promise in providing large populations with individualized dietary guidance enhancing lifestyle choices and dietary quality on a large scale. With the incorporation of personalized nutrition into health systems it is possible to target interventions such as enhancing gut health and reducing cardiometabolic risk. Personalized nutrition is better at promoting healthier diets across a variety of populations than conventional approaches as evidenced by trials such as the Food4Me trial [52]. For providing fair access and data privacy and closing evidence gaps for long-term effects broad implementation needs strong policy support and regulations. Personalized nutrition can be a paradigm-shifting public health intervention that establishes long-term health benefits in population outcomes by leveraging technology and multidisciplinary collaboration [49,53].

II.6.6 Contribution of Personalized Systems to Chronic Disease Prevention

With their ability to provide tailored dietary advice that takes into account each person’s unique risk factors and medical conditions personalized food recommendation systems have become extremely effective tools in the fight against chronic disease [53]. Particularly useful in the management and prevention of diseases like diabetes cardiovascular disease and obesity these systems serve as a link between individualized interventions and general nutritional guidelines [54].

II.6.6.1 Risk Assessment and Early Intervention

The ability to integrate risk assessment tools is a major benefit of personalized systems in the prevention of chronic diseases. Before clinical symptoms manifest these systems can identify people who are more susceptible to specific conditions and suggest suitable dietary changes by combining biomarkers genetic data and behavioral data. Wang and Hu [55] highlight that precision nutrition has the potential to provide personalized guidance for more effective prevention and management of type 2 diabetes by integrating technologies with big data analytics. Research by Celis-Morales et al. [52] demonstrated that personalized nutrition interventions produced larger and more appropriate changes in dietary behavior than conventional approaches, with participants consuming less red meat, salt, and saturated fat while increasing folate intake and achieving higher Healthy Eating Index scores.

II.6.6.2 Long-term Adherence and Lifestyle Modification

The Personalized systems overcome the major hurdles to preventing chronic diseases, which is maintaining long-term diet changes because they consider what each person likes, their culture, and their environment on a day-to-day basis. Personalized guidance can be more likely to be adhered to than generic diet advice because they consider individual preferences, cultural factors, and real-world limitations. Forster and colleagues' research in 2016 showed that giving individuals personalized dietary advice using new technology enhances eating habits. However, the extent of change depends on how frequent feedback type and frequency are [56]. Although the Food4Me study primarily examined the relationship between FTO genotype and macronutrient consumption rather than adherence dietary advice itself, it underscored the necessity of incorporating genetic elements into personalized nutrition strategies [57].

II.6.6.3 Improvement in Quality of Life and Individual Well-Being

Food recommendation systems (FRS) go beyond prevention of disease and dietary control to enhance users' daily lives, mental well-being, and satisfaction directly. Through delivering recommendations tailored to individuals' needs, these systems tackle practical, psychological, and social aspects of well-being.

1. **Enhanced Nutritional Status and Physical Performance**

   Personalized diet plans have been shown in studies that it can enhance both physical performance and nutritional status. In one randomized controlled study for example, a customized diet with or without physical exercise therapy was linked to better life quality, muscle strength, nutritional status, and physical performance in older adults who were malnourished [58].

2. **Psychological Well-Being and Satisfaction**

   Personalized nutrition can also promote positive impacts on mental health. By involving personal food choice and cultural necessity, such interventions can enhance satisfaction with the eating aspect of life, reduce stress related to eating, and enhance the overall quality of the relationship with food. Personalized control enhances the sense of autonomy and empowerment and results in overall mental well-being [59].

3. **Enhanced Nutritional Awareness and Education**

   Personalized food recommender systems promote food literacy since they offer users nutritional information of recommended meals in order to allow them to make informed diet. For example, there was a study that presented a system that integrates user preference and nutritional information to recommend daily meals, actually informing users of the nutritional value of their food [60].

II.7 Challenges and Limitations of Food Recommendation Systems

1) **Diverse and Personalized Preferences:** People's food choices are very personal. They depend on cultural, dietary needs, and personal factors. making it challenge for standard recommendation algorithms to generalize effectively.
2) **Contextual Dependence:** Depending on the time of day (e.g., breakfast vs. dinner), location, and event, food preferences can vary. Conventional algorithms usually generate recommendations that are less relevant, since they cannot take this context into account.
3) **Limited and Biased Datasets:** Food datasets may not be very diverse, typically focusing on specific types of food or certain restaurants, and therefore may lead to bias and limiting recommendation quality.
4) **Dynamic Menus and Availability:** Menu items are always changing, such as when restaurants introduce new seasonal menus, and static algorithms are unable to adapt to these changes producing recommendations that are out of-date or unrelated.
5) **Nutritional and Dietary Constraints:** Users' health-related requirements cultural dietary restrictions or allergies may need to be taken into account. These important factors are frequently ignored by standard models.
6) **Multi-Criteria Decision Making:** Taste, price, availability and healthiness are just a few of the many variables that influence food choices while standard algorithms are frequently created for recommendations based on single-criterion recommendations, struggling to handle this complexity.
7) **Additional Contextual Factors:** Some recommendations may be unfeasible because the models often do not account for constraints such as budget, seasonality, time available for cooking, or equipment.
8) **Heterogeneous and Complex Data Integration:** It can be difficult and resource-intensive to handle data from various and heterogeneous sources when incorporating contextual information [61].

II.8 Conclusion

This chapter emphasized the significance of a balanced nutrition in health promotion and disease prevention, while also confronting contemporary issues for individuals attempting to consume a healthy diet. It explained how food recommendation systems are being designed as new technologies to guide users towards healthier foods by providing recommendations on the basis of individual taste, nutritional needs, and health goals. While food recommendation systems show potential, they still face challenges concerning personalization, data quality, and contextual awareness. However, recent advances in deep learning provide powerful means for better modeling complex food-related data and user preferences for the purpose of designing more sophisticated and responsive recommendation approaches.

Chapter III
Recommendations systems based on Deep learning

III.1 Introduction

Artificial Intelligence (AI) has become a transformative force across numerous domains, driven by the explosion of data and the increasing computational power of machines. These advancements have enabled AI systems to perform tasks that once required human intelligence. One area where AI has had a particularly notable impact is in Recommendation Systems (RS), where Deep Learning (DL) methods have significantly enhanced accuracy, scalability, and personalization. This chapter explores Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL), with a specific focus on their application in food recommendation systems. We begin by examining the fundamentals of AI and various ML approaches. It also highlights the capabilities of deep learning architectures in learning complex patterns from vast and diverse datasets. Finally, we explore the transformative potential of deep learning in delivering more personalized, context-aware, and health-oriented food recommendations by reviewing recent innovative systems.

III.2 Artificial Intelligence

Artificial Intelligence (AI), a branch of computer science, aims to develop systems that mimic human intelligence by processing data, learning from experience, and solving complex problems. AI relies on data and algorithms, with subfields like Machine Learning (ML), Deep Learning (DL), Computer Vision (CV), and Natural Language Processing (NLP) enabling tasks such as image recognition, language understanding, and decision-making. AI's ability to analyze vast amounts of information quickly and accurately has made it invaluable across industries including healthcare, finance, retail, marketing, transportation, and cybersecurity. It powers applications like translation tools, fraud detection systems, personalized recommendations, autonomous vehicles, and virtual assistants. The benefits of AI include automation of repetitive tasks, reduction of human error, 24/7 availability, accelerated research, and enhanced customer experiences through personalization and intelligent support systems [62].

III.3 Machine Learning (ML)

Machine learning (ML), a subfield of artificial intelligence first termed by Arthur Samuel in 1959, involves algorithms that learn from examples and improve performance without explicit programming. Unlike conventional programming with predetermined instructions, ML systems recognize patterns and make predictions by tuning model parameters through training on historical data, enhancing their ability to generalize to new information. This technology has become essential in the 21st century as traditional analysis methods struggle with exponentially growing data volumes. ML enables extracting insights from big data, solving complex problems that resist algorithmic specification, driving innovation across domains like healthcare, finance, and retail, enhancing automation while freeing humans for creative work, and supporting scientific discovery by uncovering hidden relationships. The ML process follows a structured workflow: data collection from various sources, preprocessing to clean and structure information, model selection based on problem type and available resources, training to optimize parameters, evaluation using metrics like accuracy and precision, hyperparameter tuning for performance enhancement, and finally deployment for real-world predictions. Applications include personalized recommendations on platforms like Coursera, intelligent voice assistants such as Siri and Alexa, fraud prevention in financial institutions, and content personalization on social media platforms [63,64].

III.3.1 Types of Machine Learning

Machine learning includes four main types: supervised, unsupervised, semi-supervised, and reinforcement learning. Each type uses different data and methods to solve tasks like prediction, pattern discovery, or decision-making.

III.3.1.1 Supervised learning

The aim of supervised learning is to create a predictive model using labeled data. In this scenario, every example in the dataset comes with a known output, referred to as a label. The learning procedure takes advantage of these labels to control the training process, essentially learning a function that takes inputs and produces outputs. This involves having an underlying fixed relationship between the input data and the labels, which are tried to be approximated by the model to the best possible manner.

In supervised learning, there are several types of tasks, depending on the nature of the label. When the label can assume two values only, such as, “spam” and “not spam” the problem type is called **binary classification.** This is a common type of problem in many real-world situations such as detecting fraudulent transactions, image classification (determining whether an image contains a giraffe) or classifying an email as spam. When the label can take on more than two categories, we refer to it as **multi-class classification.** For example, this applies when the model must recognize handwritten digits, identify the language of a text, recognize a facial expression from a list, or classify types of cuisine based on recipe ingredients.

The other type of supervised learning is **regression**, where the output is a continuous value rather than a discrete category. The task in regression problems is to predict the price of a stock, estimate website traffic, or even forecast the yield of a crop. All these tasks require the model to learn and identify numerical trends and make predictions of future outcomes. In more complicated situations the expected output could be a structured object such as a vector, image, sequence or graph, rather than a single label or value. They are classified as structured output prediction or structured regression problems. Examples include creating images from input descriptions translating speech to text and automatically translating languages. Common algorithms used in these tasks include Decision Trees, Support Vector Machines (SVM), Naïve Bayes, K-Nearest Neighbors (KNN), Linear Regression, Logistic Regression, and ensemble methods like Random Forest and AdaBoost, which are used for both classification and regression problems depending on the nature of the output [65].

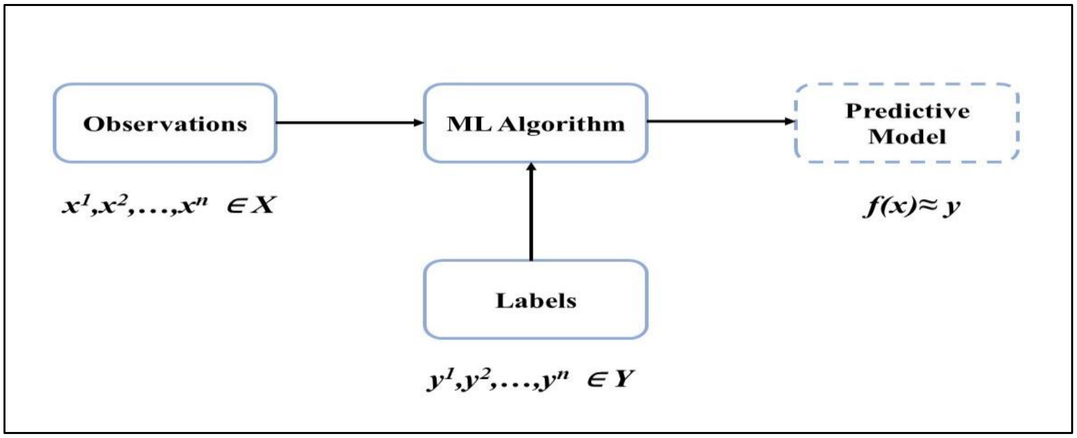


Figure III-1: Supervised Learning.

III.3.1.2 Unsupervised learning

Unsupervised learning is concerned with situations where data is provided without labels, this area of machine learning is all about modeling observations and to extract meaningful insights from them. While in supervised approaches the process proceeds with what are considered "correct" answers for the problem under consideration or study, in contrast, unsupervised learning finds relations and properties inherent to datasets. **Clustering** found in unsupervised learning is probably one of the most used and well-known techniques within this area of machine learning, with algorithms such as K-Means and Hierarchical Clustering being commonly applied to discover hidden structures in data. Clustering can be used to segment customers based on behavior, classify documents by topics, compress images by grouping similar pixels, or find subclasses of a disease based on symptoms. As part of clustering when it is utilized, the algorithm will determine which observations are similar enough in order to be grouped together.

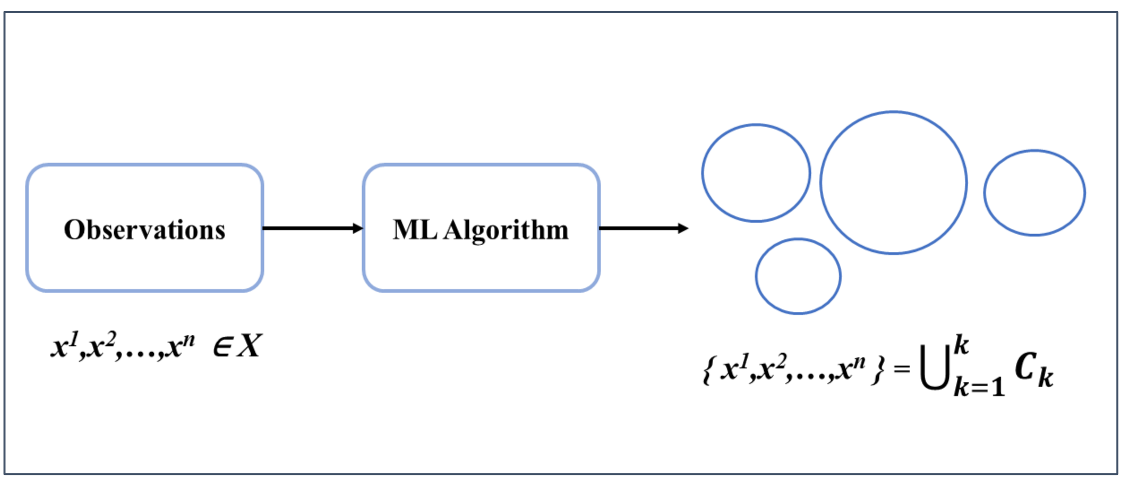


Figure III-2: Clustering.

Another important technique is **dimensionality reduction**, which aims to simplify data by transforming it into a space with fewer dimensions while preserving its essential features. This helps reduce computational cost, save memory, and can also improve the performance of future supervised learning tasks. Dimensionality reduction is often used for visualizing complex datasets or preparing them for further analysis, and a widely used algorithm for this purpose is Principal Component Analysis (PCA).

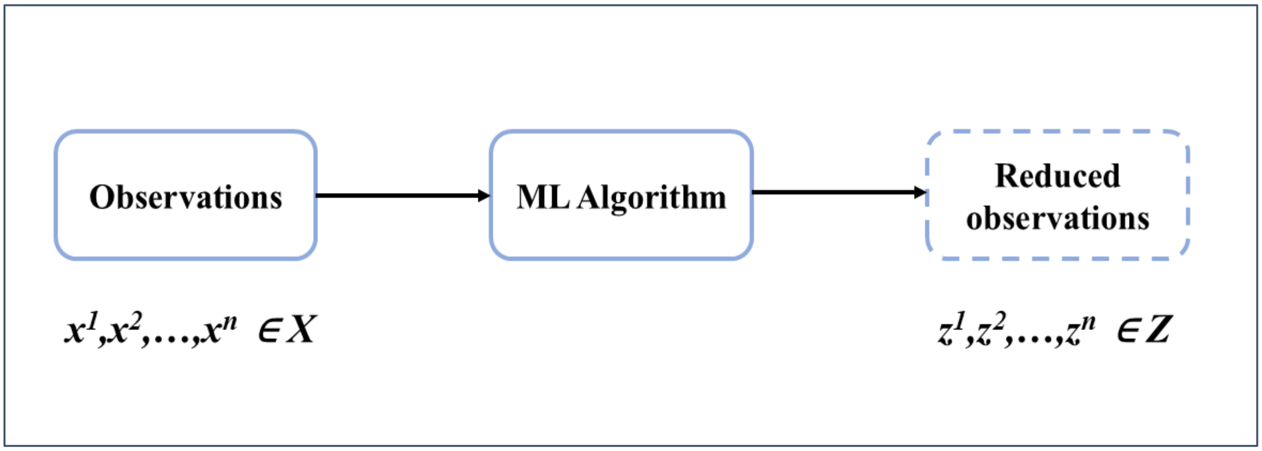


Figure III-3: Dimensionality Reduction.

III.3.1.3 Semi Supervised learning

Semi-supervised learning works with partly labeled data, offering a good trade-off between supervised and unsupervised. In that it only needs labels on a portion of the data, the technique saves human labor in data preparation but also potentially minimizes human biases otherwise maximized by complete labeling. In image classification, for example, it is possible to collect thousands of images, but labeling each one of them is expensive and time-consuming. Semi-supervised methods leverage patterns from small labeled samples to make inference on unlabeled instances, creating more powerful learning systems for real-world applications where large-scale labeling is infeasible.

III.3.1.4 Reinforcement learning

Reinforcement learning is a specific type of learning in which a system interacts with the environment by taking actions and getting its reward based on the actions taken. The reward may be positive for good actions, or negative for bad ones. The reward may sometimes arrive after a long series of actions, in a similar manner to when one learns to play a game, such as chess. The objective is to learn a policy that will provide the system with a way to choose actions that cause it to receive the maximum reward over time. Reinforcement learning is predominantly applied in games and robots [65].

Table III-1: Key Differences Between Machine Learning Approaches.

Factor	Supervised	Unsupervised	Semi-Supervised	Reinforcement
Input	Labeled data	Unlabeled data	Both labeled & unlabeled	Interaction-based
Complexity	High complexity	Low complexity	Medium complexity	High and dynamic
Classes	Known classes	Unknown classes	Some known classes	No predefined classes
Accuracy	Very accurate	Moderately accurate	Balanced accuracy	Learns over time

III.4 Deep Learning

Deep learning, a sophisticated subfield of machine learning, enables computers to learn tasks by examining examples rather than following explicit instructions. Built on artificial neural networks inspired by the human brain, deep learning systems consist of interconnected layers of information-processing nodes: an input layer that receives raw data, one or more hidden layers that transform this data using learned weights and activation functions, and an output layer that produces final predictions.

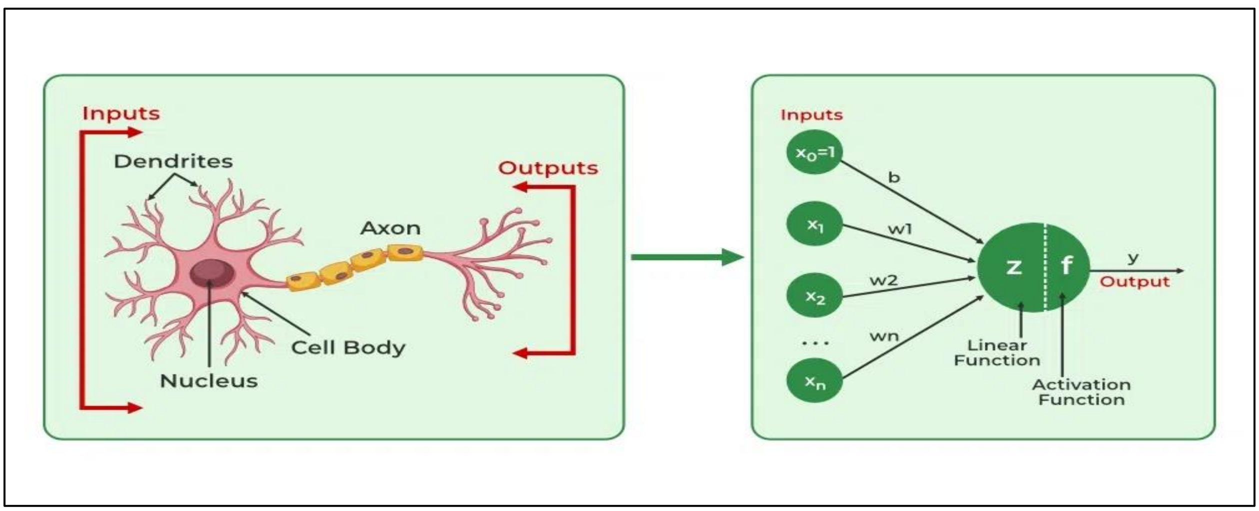


Figure III-4: Biological neurons to Artificial neurons.

The term "deep" refers to the multiple processing layers that allow the system to recognize increasingly complex patterns and levels of abstraction. During training, data moves through the network via forward propagation, generating outputs that are compared to actual values using loss functions. The network then employs backpropagation to fine-tune internal weights and improve accuracy as it processes more examples. Deep learning's revolutionary importance stems from its ability to efficiently process unstructured data (images, text, voice) without extensive standardization, analyze large datasets at unprecedented speeds using GPUs, achieve superior accuracy in applications like computer vision and natural language processing, and automatically detect patterns with minimal human intervention. Applications include computer vision for facial recognition and medical imaging, natural language processing for chatbots and translation, generative AI for creating new content like text and art, and time series forecasting for predicting market trends and weather events [66,67].

III.4.1 Components of Deep Learning Models

1. Layers

Layers are the core elements of deep learning models, responsible for processing and transforming data as it passes through the network. A typical model includes an input layer, multiple hidden layers, and an output layer. The input layer receives raw data, which then flows through the hidden layers where the model learns to extract relevant features. Specialized layers, such as convolutional layers in CNNs, capture spatial patterns in image data. Recurrent layers in RNNs, LSTMs, and GRUs capture temporal dependencies in sequential data. Dense layers, commonly found in the final stages, allow for high-level reasoning by connecting every neuron in one layer to all neurons in the previous layer [68].

2. Loss functions

Loss functions measure the difference between the model's predictions and actual target values, guiding the optimization process. Some commonly used loss functions include:

- **Mean Squared Error (MSE)** is commonly used in regression tasks. It calculates the average of the squared differences between the predicted and actual values, penalizing larger errors more strongly. Its formula is:

$$MSE = \frac{1}{n}\sum_{i}^{n}(y_i - \hat{y}_i)^2$$

Where:

- n is the number of samples.
- y_i is the true value.
- $\hat{y}_i$ is the predicted value.

- **Cross-Entropy Loss** is widely used for classification tasks. It measures how different the predicted probability distribution is from the actual label distribution. It is especially effective in binary and multi-class classification. The formula is:

$$Cross\ Entropy = -\sum_{i} p(y_i) \log q(y_i)$$

Where:

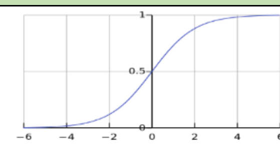
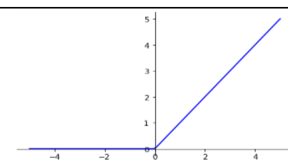
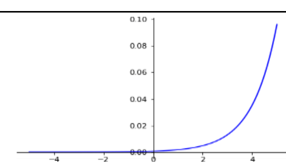
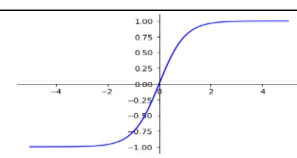
  - $p(y_i)$ is the true class (one-hot encoded vector).
  - $q(y_i)$ is the predicted probability distribution.

- **Huber Loss**: Combines the advantages of MSE and MAE by being quadratic for small errors and linear for large errors, making it robust against outliers [68]. Its formula is:

$$Huber\ Loss = \begin{cases} \frac{1}{2}\,(y_i - \hat{y}_i)^2, & for\ |y_i - \hat{y}_i| \le \delta \\ \delta\left(|y_i - \hat{y}_i| - \frac{1}{2}\,\delta\right), & otherwise \end{cases}$$

3. Activation Functions

Table III-2: Summary of Common Activation Functions in Deep Learning.

Activation Function	Description	Formula	Graphic
Sigmoid	Maps input to the range (0, 1). Commonly used in binary classification tasks where the output represents a probability	$\sigma(x) = \dfrac{1}{1 + e^{-x}}$	
ReLU	Outputs zero for negative inputs and the input itself for positive values. Range is [0, ∞).	$ReLU(x) = \max(0, x)$	
Softmax	Converts a vector of values into probabilities that sum to 1. Output range is (0, 1) for each class. Used in the output layer of multi-class classification problems.	$softmax(z_i) = \dfrac{e^{z_i}}{\sum_j e^{z_j}}$	
Tanh	Maps input to the range (-1, 1). Often used in RNNs and hidden layers where centered outputs help with optimization	$f(x) = \dfrac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$	

4. Optimization Algorithms

The optimization algorithms perform parameter adjustments to reduce the loss function while enhancing the model execution. Some key optimization algorithms include:

- **Stochastic Gradient Descent (SGD**) utilizes learning rates to adjust parameters through gradients computed from mini-batch. It exploits mini-batches instead of the entire dataset for reducing computational expense, though it may be sensitive to the choice of learning rate and may struggle with finding global minima.
- **The Adaptive Gradient Algorithm (AdaGrad)** adjusts parameter learning rates using gradient information from past iterations which makes it suitable for working with sparse data.
- **RMSProp (Root Mean Square Propagation)** establishes an adaptive framework by using moving average calculations of squared gradients to stop the learning rate from diminishing too quickly.
- **The Adaptive Moment Estimation (Adam)** unites adaptive learning rates (from AdaGrad) with squared gradients (from RMSProp). This optimization method holds individual adaptive rates for each parameter which renders it a widely adopted solution for managing sparse gradients and accelerating convergence [68].

5. Backpropagation

Backpropagation is an important algorithm for training multilayer neural networks. It achieves this by adjusting the weights in the network and minimizing the output error. The algorithm begins with random initialization of the weights. Then, during feedforward pass the input is propagated through the layers of the neural network to produce a predicted output. This predicted output is compared against the target actual output to calculate the prediction error. At this point the backward pass then begins. Backpropagation propagates the prediction error backwards through the layers of the neural network, layer by layer and computes how much each weight contributed to the prediction error. This information is then used to update the weights to decrease prediction error in subsequent predictions [69].

6. Generalization Challenges and Regularization Techniques

The goal of deep learning models is to produce performance excellence in training data as well as unknown data which represents generalization ability. Two main issues affect models:

- **Overfitting** happens when the model learns training data with excessive detail including noise and random variations, they develop overfitting instead of understanding the underlying patterns. New and unknown data perform poorly under the model since it has incorporated training data into its memory system.

- **Underfitting** occurs when the model is too simple to capture the underlying patterns in the data. It performs poorly even on the training data, making it ineffective for validation or test data as well. This usually signals the need for a more complex model or additional features [70].

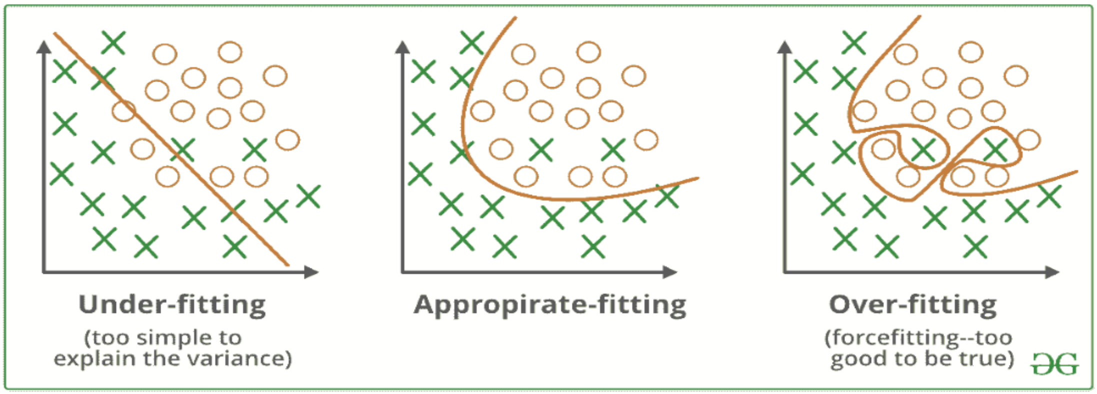


Figure III-5: Model Fitting Deep Learning.

To Regularization techniques serve as a common solution to resolve these problems while improving generalization abilities and preventing model dependence on particular training examples.

- **Common Regularization Techniques:**
    - **Lasso Regression (L1 Regularization)** Least Absolute Shrinkage and Selection Operator implements the absolute value of feature weights as additional elements in the loss function evaluation. Through its implementation L1 Regularization functions to both minimize overfitting and select features through setting coefficient values to zero.
    - **Ridge Regression (L2 Regularization)** Ridge regression includes an addition of squared weight values into the loss function. It reduces coefficient values instead of permanently removing them from the model which enables its use across features that help predict the output.
    - **Elastic Net Regression** combines the regularization strength of L1 and L2 penalties in a single model framework. This method relies on a hyper parameter to establish the level of interaction between L1 and L2 regularization [70].
    - **Dropout** randomly disables a percentage of neurons during training, which effectively avoids over-reliance on a few neurons and pushes the model to learn a more general and robust represented feature.
    - **Batch Normalization** adjusts and scales the outputs from layers to reduce internal covariate shift. By implementing this technique, the training process becomes more efficient while achieving better performance and establishing more stable parameter values.

- **Early Stopping** keeps track of the performance of the model on the validation set and halts training when that performance begins to decrease, regardless of the continuous improvement observed on the training data. Early stopping mitigates overfitting by stopping the training of the model before the model memorizes the training set.
- **Data Augmentation** serves as a technique which expands dataset diversity through various modifications made to input data. Images can benefit from such data augmentation methods like rotation and flipping and scaling [71].

III.4.2 Deep Learning Architectures

- **Artificial Neural Network (ANN)**

Artificial neural networks create digital versions of biological neural networks with their functionality based on human brain structures. Neural networks consist of extensive quantities of artificial neurons that arrange themselves into different layers which serve as information channels for processing. The basic structure of artificial neural networks depends on an input layer and one or more hidden layers as well as an output layer while hidden layers function to transport information received from the input layer to the output layer. The functionality of artificial neural networks depends on hidden layers which turn raw input data into useful output data by establishing hidden representations from the original input. Neurons maintain weight values to represent their strength of impact on other neurons which backpropagation modifies during training processes. The learning process of ANNs enables them to discover hidden patterns in data which makes them effective tools for image recognition and natural language processing as well as recommendation systems. The model's capability to change weights represents the core principle for developing ANN learning and prediction abilities so that performance increases over time [72].

Table III-3: Comparison of Artificial vs Biological Neurons.

Component	Biological Neuron	Artificial Neuron
Structure	Dendrites → Cell body (Soma) → Axon	Inputs → Nodes → Output
Receiving signals	Dendrites	Input nodes
Processing center	Cell nucleus/Soma	Nodes
Connections	Synapses	Weights
Transmitting output	Axon	Output
Learning mechanism	Synaptic plasticity	Backpropagation
Activation	Firing when threshold is reached	Mathematical activation functions

- **Multilayer Perceptron (MLP)**

The Multilayer Perceptron (MLP) serves as one of the best-known neural network structures due to its enhanced learning capacity and architectural flexibility. This neural network architecture takes a feedforward design which combines layers of neurons into input layers with hidden layers and output layers. Each neuron within a layer maintains connections to every single neuron in the subsequent layer to facilitate information transmission in a forward direction. The universal approximation ability of MLP networks allows them to approximate any continuous bounded differentiable nonlinear function precisely through sufficient numbers of neurons. MLP models exhibit high functionality in tasks including classification and regression and function approximation. The hidden layer uses nonlinear activation functions to create complex mapping capabilities while training occurs with backpropagation algorithms alongside gradient descent optimization. This architecture works successfully across multiple domains because of its ability to model complex input-output relationships [69].

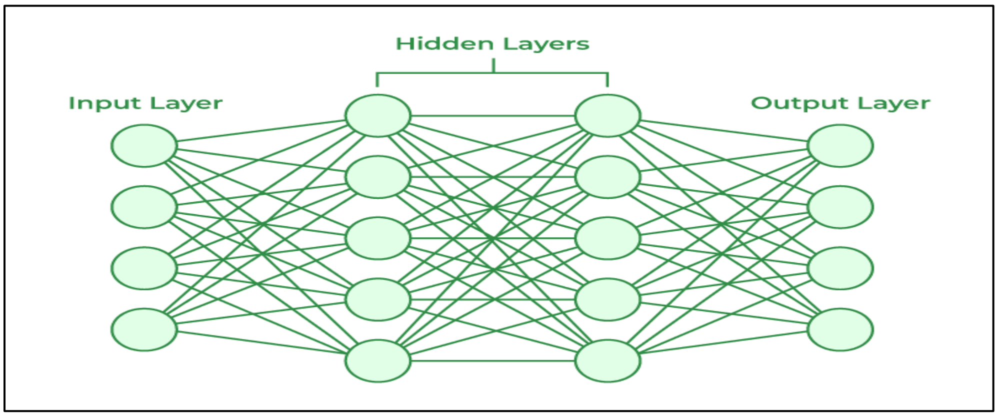


Figure III-6: Multilayer Perceptron Architecture.

- **Convolutional Neural Network (CNN)**

The deep learning model Convolutional Neural Networks (CNNs) specializes in analyzing data formats where information is arranged in grids like images and sequences and time-series and text data. An inspiration from human visual processing leads CNNs towards learning meaningful patterns from raw input data through multiple layers in which each layer assigns a single purpose. The typical CNN is simply built in such a way that it specializes in capturing local and hierarchical features while making use of a fewer number of parameters than a standard deep neural network. So, they are highly efficient and effective for structured data. The basic structure of a CNN typically consists of three types of layers:

- **Convolutional layers** scan across inputs with small filters for the purpose of feature extraction like edges, textures, or particular patterns. These features become more abstract in deeper layers.

- **Pooling layers** reduce feature map size through down-sampling that identifies either the maximum value or calculates the average of each selected group. The pooling process reduces computational requirements while simultaneously preventing overfitting.
- **Fully connected layers:** process the higher-level features that previous layers have distinguished while making final prediction outputs (such as classification or regression) in these layers.

CNNs display powerful capability yet they demand significant data labeling together with extensive computational power that has led researchers to develop more efficient deep learning techniques [73].

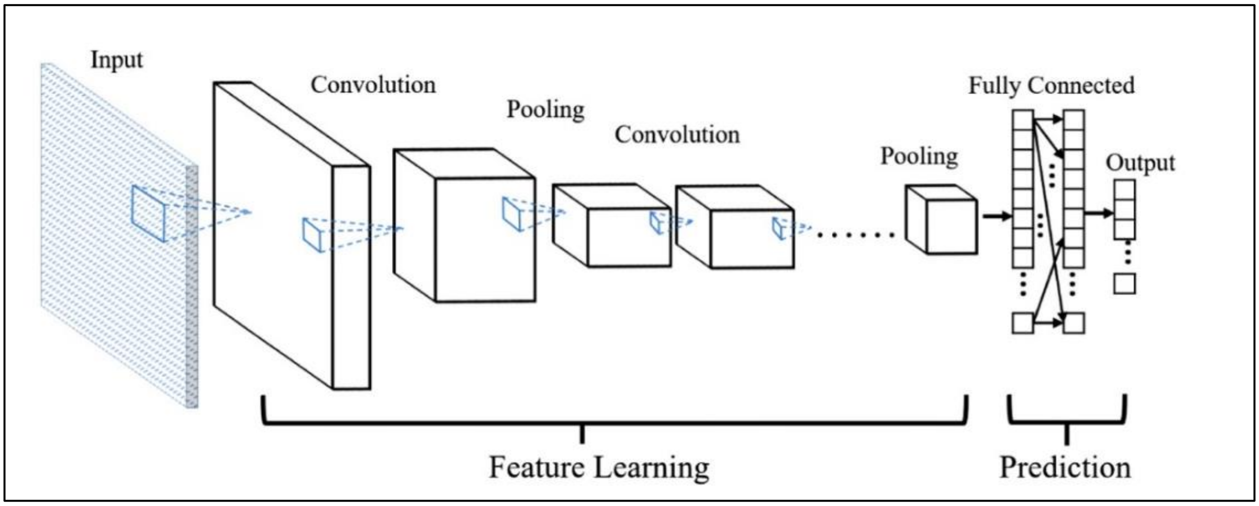


Figure III-8: CNN Architecture [68].

- **Recurrent Neural Network (RNN)**

Recurrent Neural Networks (RNNs) serve as specialized deep learning models for processing sequential data to perform tasks across natural language processing and timeseries prediction. The networks store information about past time steps as hidden state elements which enables them to discover temporal relationships. There are several key variants of RNNs designed to address limitations:

- **Long Short-Term Memory (LSTM)** networks have a memory cell that stores information across time and use gates (input, forget, output) to control data flow, and are particularly suited to tasks like speech recognition.
- **Gated Recurrent Units (GRU)** represent a simpler version of LSTMs which utilize update and reset gates to manage information flow during training and deliver equivalent performance at accelerated speeds [68].

- **Autoencoder (AE)**

An autoencoder represents a neural network structure designed to minimize data volume by extracting vital characteristics. The two essential components of an autoencoder consist of an encoder that converts initial data to latent representation values while the decoder attempts to rebuild the initial data from those representations. The network trains to minimize input-output differences to produce outputs which closely match inputs. The autoencoding system finds multiple practical applications in data compression as well as image denoising and large dataset feature extraction [68].

- **Variational Autoencoder (VAE)**

A variational autoencoder represents a specific autoencoder design which includes probabilistic systems for learning. A variational autoencoder shifts away from generating single static outputs in the hidden layer by producing probabilistic ranges of values drawn from normal distributions. The model selects samples from this established range to produce final outputs. The approach enables models to understand smoother and more flexible patterns which makes it effective for new data generation as well as detection of unusual dataset elements [68].

- **Generative Adversarial Network (GAN)**

Generative Adversarial Networks (GANs) are neural networks that consist of a generator designed to create synthetic data while a discriminator works to identify authentic and fabricated data points. The network training process works in collaboration because the generator enhances its performance by deceiving the discriminator and the discriminator improves its performance through detecting fake input. As training progresses the generator develops increasingly realistic results. Despite early challenges like unstable training, GANs have shown impressive results, especially in image generation, and are now widely used in design, gaming, and synthetic media creation [73].

- **Transformer**

The deep learning architecture Transformers introduced to enhances NLP sequence processing capabilities. The self-attention mechanisms that Transformer operates with enable simultaneous processing of input and enhance efficiency during training operations unlike RNNs. The new architectural design of transformers allows them to focus on important input elements thus producing results that enhance the effectiveness of models BERT and GPT for tasks including classification, question answering and text generation. Transformers serve applications beyond language processing by offering capabilities for computer vision, speech recognition, and financial forecasting. Their ability to scale and achieve high accuracy has made transformers crucial for modern AI systems, enabling powerful generative models and contributing significantly to the evolution of deep learning [68].

- **Graph Neural Networks (GNN)**

The processing architecture of Graph Neural Networks (GNNs) functions to understand both node information and network bond relationships between nodes. GNNs differ from traditional networks since they extract information from adjacent nodes which enables them to develop elaborate node representations. GNNs show exceptional performance in various fields including social networks and chemistry as well as communication systems. GNNs find their application in three different areas: node classification for user profiling, link prediction for recommendation systems and graph classification for drug discovery tasks. GNNs demonstrate superior performance than traditional models for relational tasks because of their capacity to understand complex network patterns thus becoming key analytic tools for multiple scientific and industrial domains [68].

III.5 Food Recommendation Systems Using Deep Learning

Recently, there has been a surge of food recommendation system research involving deep learning for generating context-aware, health-focused, and personalized nutritional suggestions. Below are notable systems and their architectural approaches:

MenuAI is one of such notable works, introducing a transformer-based deep learning architecture with Optical Character Recognition (OCR) to digitize menus at restaurants and make food recommendations according to users' nutritional needs and contextual inputs such as the time of day MenuAI's model is able to rank both historical and novel items, demonstrating strong performance in ranking on the MenuRank dataset and signaling the promise of the transformers' application to food recommendation problems [74].

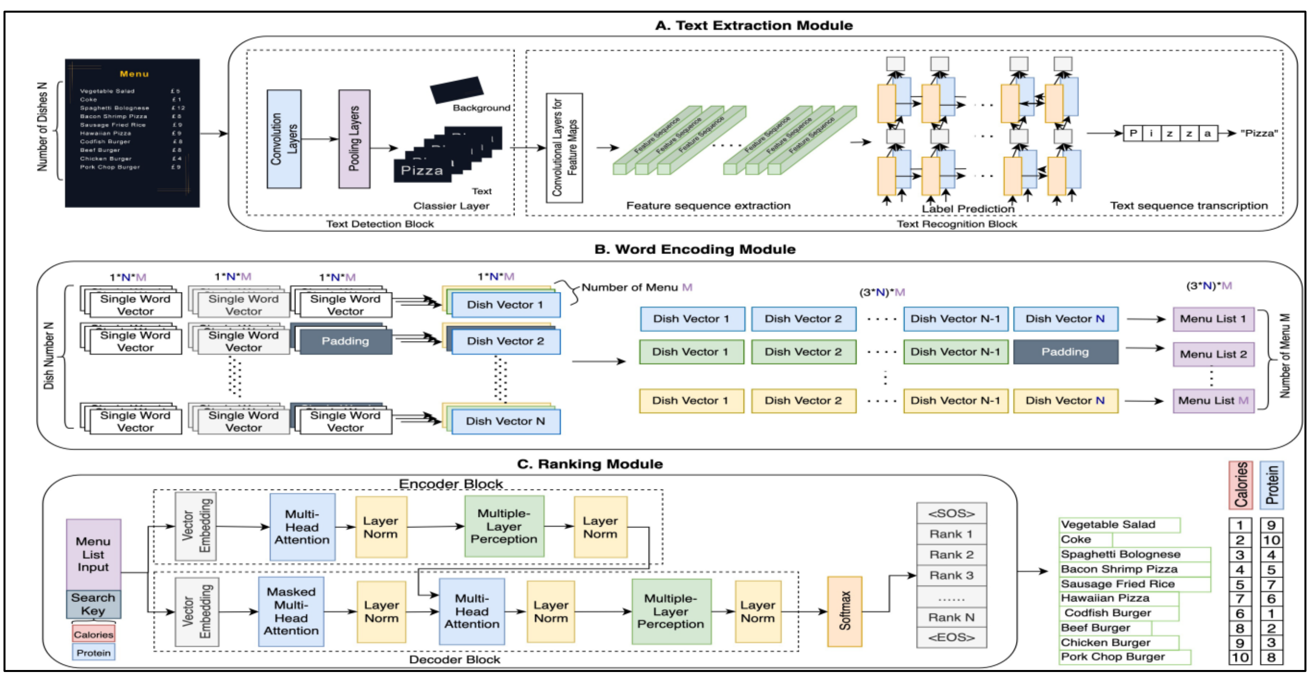


Figure III-9: The network architecture of MenuAI [74].

Another significant contribution is the explainable food recommender system developed by Rostami et al [75]. that uses deep image clustering and community detection in order to have improved recommendation quality. This is achieved through incorporating visual features obtained from food image data and a rule-based module for explainability, which contributes to higher interpretability and transparency as well as performance metrics of precision and recall compared to standard methods,

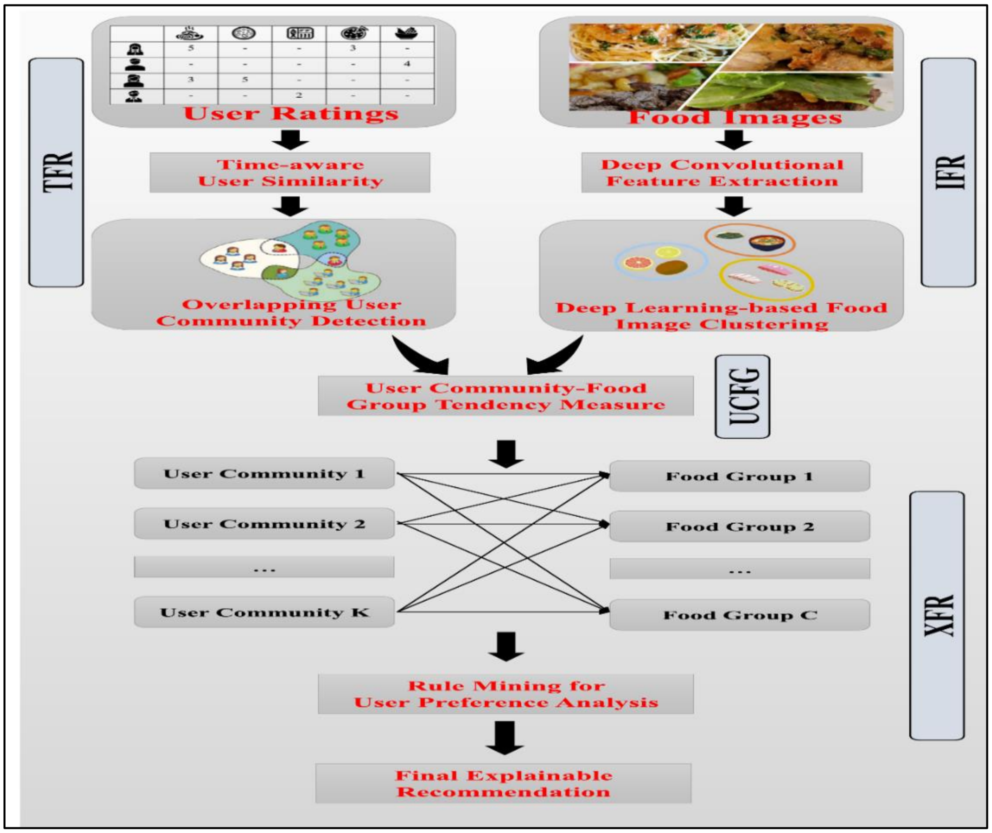


Figure III-10: Conceptual framework of the explainable food recommender system [75].

Graph neural networks (GNNs) have also been examined based on their ability to represent complex relationships between users, recipes, and nutrient information. For instance, a graph-aware food recommendation algorithm for nutrition knowledge graph leveraging the power of GCNs was introduced to include nutrition information as well as user interest, making healthier and more diversified recommendations than baseline deep learning models [76].

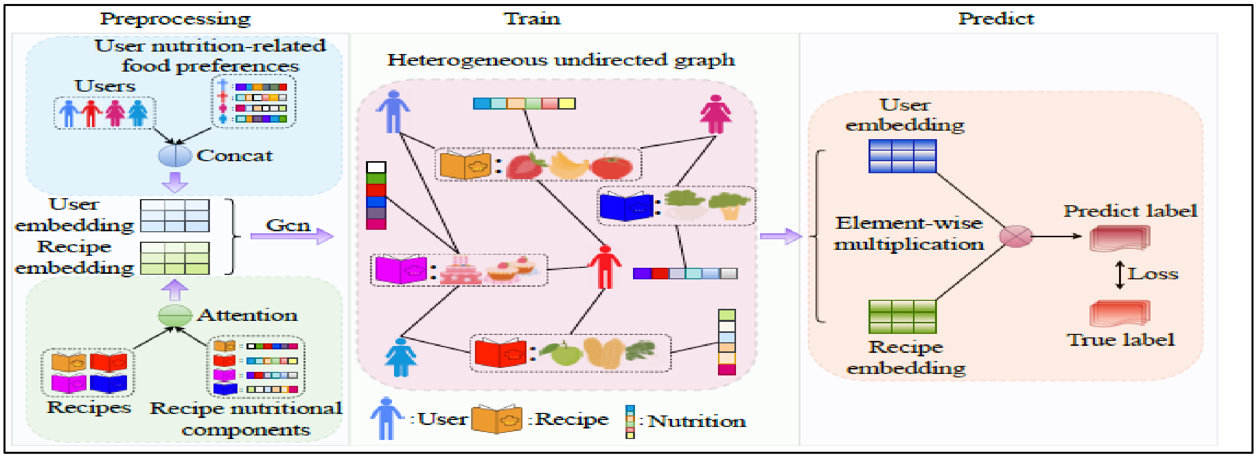


Figure III-11: Overall architecture of the developed system [76].

The Market2Dish system addresses the challenge of personalized, health-aware food recommendation by mapping available ingredients to healthy dishes. It uses recipe retrieval, user health profiling via social network data, and a category-aware hierarchical memory network to learn health-aware user-recipe interactions, offering personalized food suggestions based on individual health conditions. The paper introduces a word-class interaction mechanism to handle sparse health-related information, demonstrating the effectiveness of the approach on two newly constructed datasets [77].

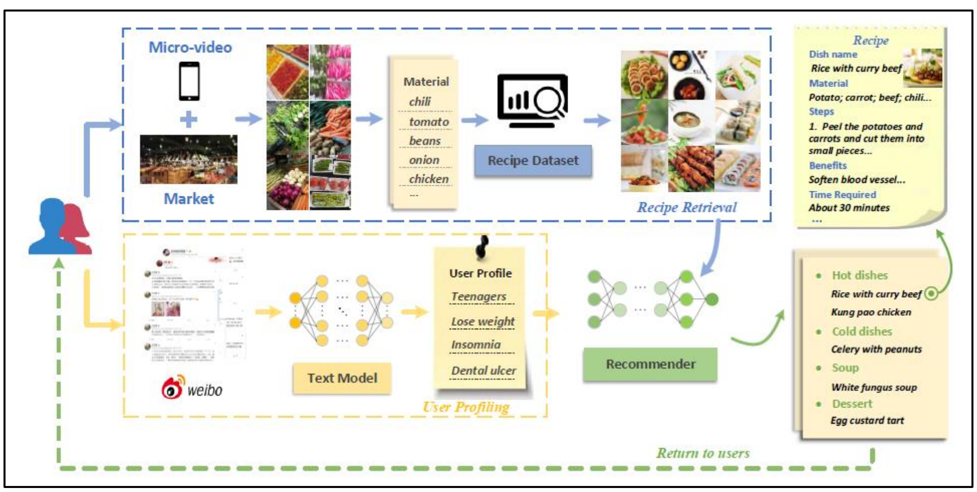


Figure III-12: Illustration of Market2Dish scheme [77].

However, although such systems significantly enhance personalization, explainability, and health-awareness, the majority of them tend to optimize either user taste or nutritional attributes individually, but not both objective functions simultaneously. This limitation triggers the development of multi-objective food recommendation system that aims for balanced integration of user taste preferences and nutritional values to promote healthier consumption with no compromise on personalization.

III.6 Conclusion

To conclude the chapter explored how artificial intelligence, machine learning and deep learning technologies are being used to develop food recommendation systems. The chapter explored several ML paradigms and deep learning architectures, which are changing the way complex data is processed and recommendations are generated. The review of innovative food recommendation systems demonstrated that there have been major advances in personalization and context awareness. However, one major limitation still exists; most systems only optimize for taste preferences or nutritional value, but rarely focus on both at the same time. This gap presents an opportunity for multi-objective approaches that could potentially change the way food is discovered and how nutrition is interpreted at the individual level by balancing enjoyment and health benefits.

Chapter IV
Methodology and Implementation

IV.1 Introduction

As personal dietary needs and health-related preferences grow increasingly prevalent, food recommendation systems are evolving into more robust tools to align user preferences with nutritional objectives. In this chapter, we describe the implementation of a hybrid food recommendation system based on the NeuMF (Neural Matrix Factorization) architecture. We introduce two primary approaches: the first, integrates health-related features directly during the model training phase. The second, applies a health score after NeuMF generates predictions, combining this factor with the predicted ratings to produce final recommendations. Additionally, the chapter details the preprocessing steps, model architecture, training procedure, and evaluation framework.

IV.2 Constraints and limitations

Food Recommender Systems (FRS) represent a recent class of intelligent applications designed to enhance individuals' quality of life by supporting healthier and more personalized dietary choices. Their importance stems from the vital role that nutrition plays in promoting public health and preventing chronic diseases such as obesity, diabetes and hypertension. According to the World Health Organization (WHO), malnutrition, whether due to undernutrition or overnutrition, poses a direct threat to human health and development, compromising the ability to perform daily physical and cognitive tasks effectively[1].

These systems function by analyzing data from multiple sources, including users' health profiles, dietary preferences, nutritional information of ingredients and eating behaviors, in order to provide personalized meal or recipe recommendations. Instead of generating arbitrary suggestions, they aim to balance nutritional value with palatability, which represents a complex and multifaceted challenge. Despite notable advancements in the field, food recommender systems still face several limitations that hinder their effectiveness and widespread adoption. One of the main challenges lies in accurately modeling users, which requires a deep and continuously updated understanding of an individual's health status, allergies, dietary goals and cultural or religious food restrictions. Collecting and maintaining such data over time often proves difficult and unreliable. Moreover, these systems frequently depend on inconsistent or low-quality nutritional data, as sources may vary in terms of accuracy, completeness and format. Some recipes lack detailed nutritional values or include vague or unspecified ingredients. A further challenge arises in aligning nutritional guidance with users' taste preferences, since people are unlikely to choose healthy options, they do not enjoy. This underlines the importance of recommendation algorithms that integrate both health and sensory dimensions.

Cultural and geographical factors are also often neglected. Many systems do not adequately reflect regional dietary habits or the availability of ingredients, which may result in suggestions that are irrelevant or culturally inappropriate. In addition, privacy and ethical concerns are significant, especially since these systems handle sensitive personal data related to health and behavior. This situation raises important issues regarding data protection, informed consent and transparency in data usage. Another difficulty is the lack of clarity in how recommendations are generated. Many systems do not explain why a specific dish is suggested, which can reduce user

1: https://www.who.int/news-room/fact-sheets/detail/malnutrition trust and engagement. Limited diversity in suggestions and repetitive outputs may also contribute to user fatigue and limit long-term effectiveness. It is therefore essential to develop advanced methods that promote both novelty and relevance in recommendations [80].

IV.3 Methodology

In this project, we address one of the most important issues previously raised: how to find a balance between user preferences and their health. To achieve this, a hybrid food recommendation model is implemented, based on Neural Matrix Factorization (NeuMF) [30] combining collaborative filtering and content-based approaches. The system leverages two distinct NeuMF models:

- A **pre-filtering model**, which directly incorporates health score feature during the training of the NeuMF model. This model aims to learn personalized preferences while taking into account the user's health aspects.
- A **post-filtering model**, which applies a health score after NeuMF predicts the rating. This factor is linearly combined with the initial prediction to produce the final rating.

Both models share a common architecture, composed of the following components:

- Generalized Matrix Factorization (GMF): Captures linear interactions between users and items.
- Multi-Layer Perceptron (MLP): Learns complex, non-linear relationships.
- Neural Matrix Factorization (NeuMF): Fuses the outputs of GMF and MLP through a neural network to generate the final rating predictions.

IV.3.1 GMF Branch

The **Generalized Matrix Factorization (GMF) branch** is a neural extension of traditional matrix factorization techniques widely used in collaborative filtering. It models the interaction between users and recipes by learning latent embedding vectors for each entity. Let $\boldsymbol{p_u}$ be the embedding of user $\boldsymbol{u}$, and $\boldsymbol{q_r}$ be the embedding of recipe r.The interaction between the user and the recipe is captured by the element-wise product of these two vectors, denoted by the symbol $\odot$:

$$\emptyset_{GMF} = \boldsymbol{p_u} \odot \boldsymbol{q_r}$$

This interaction vector $\emptyset_1$represents how each latent feature of the user aligns with the corresponding feature of the recipe.

IV.3.2 MLP Branch

The Multi-Layer Perceptron (MLP) branch captures complex, non-linear interactions between users and recipes by processing a combination of collaborative and content-based features. The core inputs to the MLP include the user embedding $\boldsymbol{p_u}$, the recipe embedding $\boldsymbol{q_r}$, and a vector representation of the recipe's ingredients $\boldsymbol{f_{ing}}$, which is computed as the average of individual ingredient embeddings.

In the pre-filtering model, an additional health score feature vector $\boldsymbol{f_{hf}}$ derived from nutritional information is included. This allows the model to incorporate health considerations directly into the learning process, enabling the prediction function to adapt to both user preferences and dietary constraints. In contrast, the post-filtering model excludes $\boldsymbol{f_{hf}}$ from the MLP input and applies health adjustment after the NeuMF model makes its initial prediction.

The input to the MLP in the pre-filtering model is thus:

$$z_{1=}\emptyset_1\left(p_u, q_r, f_{ing}, f_{hf}\right) = \begin{bmatrix} p_u \\ q_r \\ f_{ing} \\ f_{hf} \end{bmatrix}$$

And in the post-filtering model:

$$z_1 = \emptyset_1\left(p_u, q_r, f_{ing}\right) = \begin{bmatrix} p_u \\ q_r \\ f_{ing} \end{bmatrix}$$

This input vector is passed through multiple fully connected layers using ReLU activations to introduce non-linearity:

$$\emptyset_2(z_1) = a_2(W_2^T z_1 + b_2)$$

$$\ldots\ldots$$

$$\emptyset_L(z_L - 1) = a_L(W_L^T z_{L-1} + b_L)$$

Finally, the MLP branch produces the predicted preference $\hat{y}_{ur}$ by applying a sigmoid activation function $\boldsymbol{\sigma}$ on the output of the last hidden layer:

$$\hat{y}_{ur} = \sigma(h^T \emptyset_L(z_L - 1))$$

IV.3.3 NeuMF Model

In both NeuMF-based models, the outputs of the GMF and MLP branches are fused via vector concatenation to form a comprehensive latent representation. Specifically, the GMF output is defined as the element-wise product of user and recipe embeddings:

$$\emptyset_{\boldsymbol{GMF}} = \boldsymbol{p_u} \odot \boldsymbol{q_r}$$

The MLP output is obtained by passing the concatenated input vector z_1 (defined earlier in Section IV.3.2) through L fully connected layers with ReLU activations:

$$\emptyset_{MLP} = a_L(W_L^T a_{L-1}((\ldots a_2(W_2^T z_1 + b_2) \ldots)) + b_L)$$

The fused representation is then formed by concatenating the GMF and MLP outputs:

$$z_{NeuMF} = \begin{bmatrix} \emptyset_{GMF} \\ \emptyset_{MLP} \end{bmatrix}$$

Finally, the predicted preference $\hat{y}_{ur}$ is computed by applying a sigmoid activation on a linear transformation of the fused vector:

$$\hat{y}_{ur} = \sigma(h^T z_{NeuMF})$$

In the **pre-filtering model**, health score feature is incorporated directly into the MLP input. As a result, the prediction $\hat{y}_{ur}$ inherently reflects a balance between user preference and health-aware considerations, learned during model training.

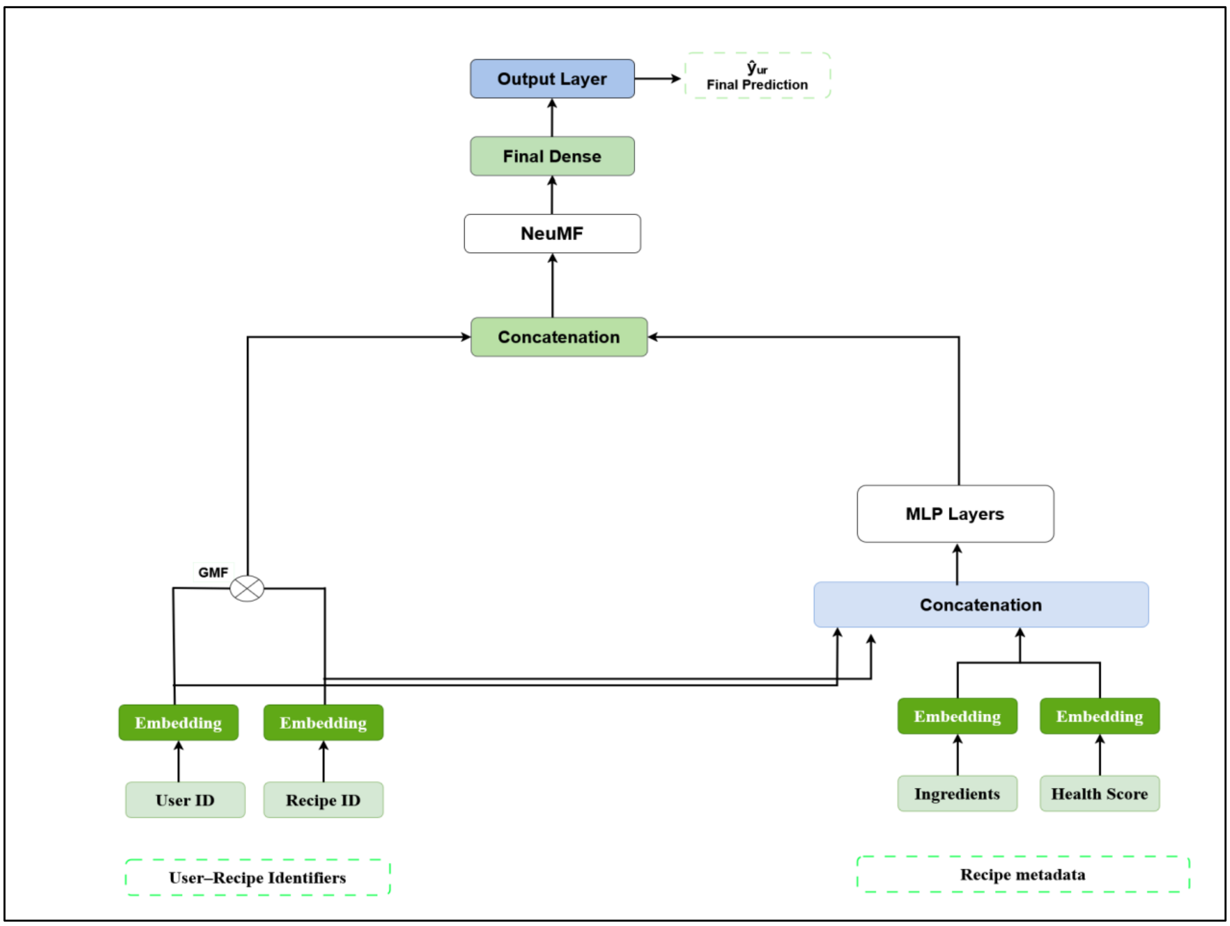


Figure IV-1: The Pre Filtering Model Architecture.

In contrast, the **post-filtering model** excludes health score from the training inputs. Instead, after computing $\hat{y}_{ur}$, the model applies a linear reweighting that blends the preference score with an independently computed health score h_f:

$$y_{final=} \alpha * \hat{y}_{ur} + (1 - \alpha) * h_f$$

where $\alpha \in [0,1]$ is a tunable hyperparameter that controls the trade-off between user preference and healthiness in the final recommendation output. This flexible fusion design allows the system to adapt to different recommendation goals favoring either pure user preferences or a more health-conscious balance without retraining the entire model.

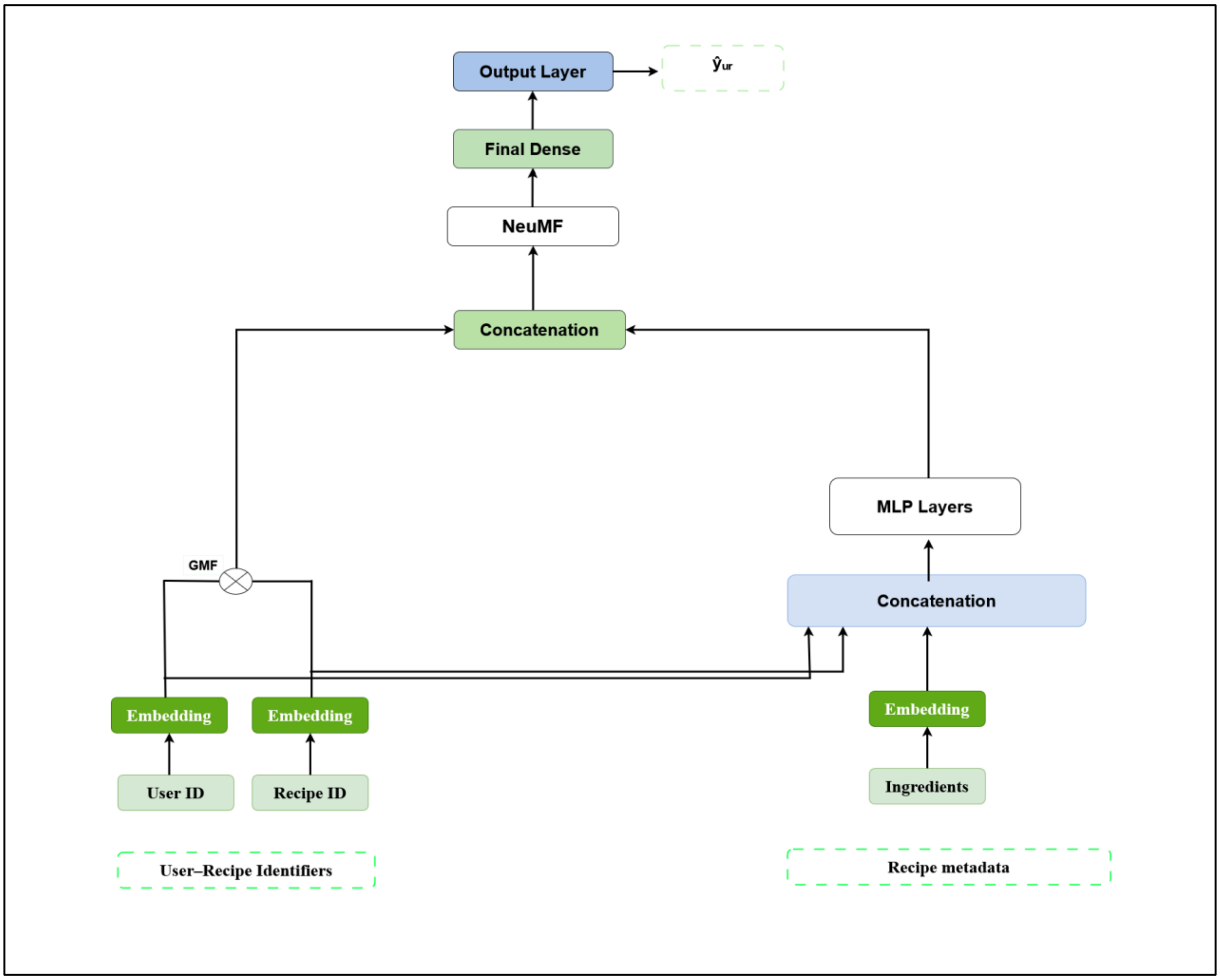


Figure IV-2: The Post Filtering Model Architecture.

IV.3.4 Baseline NeuMF Model

To establish a performance baseline, a simpler NeuMF model was also implemented using only user and recipe IDs as input. This version excludes all content-based features such as ingredients or health score, relying solely on collaborative filtering signals. The architecture is identical in structure to the main NeuMF models, utilizing GMF and MLP branches, but only user and item embeddings are fed into both components. This baseline serves to evaluate the performance gain achieved by incorporating nutritional and contextual features in the pre- and post-filtering models.

IV.4 Implementation Environment and Tools

IV.4.1 Python

Python is a high-level programming language that is universal and open-source, created by Guido van Rossum and released for the first time in 1991. Python supports various programming paradigms, including procedural, object-oriented, and functional programming. Python is valued for its easy and readable syntax, mirroring English and using indentation to define code structure, hence making coding maintenance simple. It's cross-platform; it can be used on Windows, macOS, Linux, etc. Python is used in many fields, including web development, software development, data analysis, system scripting, and rapid prototyping. Its interpreted nature enables simultaneous code execution which speeds up testing and development. Python is a versatile language for a wide range of implementation environments thanks to its functionality to manipulate databases, files, and complex numerical computations [78].

IV.4.2 NumPy

NumPy is a fundamental Python library for numerical computation, particularly efficient handling and processing of large matrices and multi-dimensional arrays. Travis Oliphant introduced NumPy in 2005 and provides the ndarray object which is high-performance capable much quicker compared to typical Python lists due to the fact that memory is stored contiguously and implemented efficiently with C and C++. It covers a wide range of mathematical functions that are useful to use in applications such as Fourier transforms and linear algebra. NumPy is used in data science and scientific computing worldwide due to its usability, performance, and because it can seamlessly be integrated into Python-based workflows [78].

IV.4.3 Pandas

Pandas is a powerful library important to Python, originally created by Wes McKinney in 2008, that was built for data manipulation and data analysis. It provides data structures such as Series and DataFrames that allow a programmer to handle, clean, and explore a dataset with ease and speed. Specifically, Pandas can be useful to find the correlation between data, the mean, maximum, and minimum of a data set, or to clean data by removing irrelevant tuples or null values. It is widely used in the field of data science as it will help make sense of the data and make it a better resource for future analysis and decision making [78].

IV.4.4 PyTorch

PyTorch is a widely adopted and user-friendly deep learning framework. It utilizes tensors multi-dimensional arrays similar to NumPy arrays, to perform efficient numerical computations, leveraging GPU acceleration for enhanced performance. Primarily employed for developing deep learning models and complex machine learning applications, PyTorch has become a go-to tool for many in the field. Academic researchers favor PyTorch for its flexibility and intuitive interface, which facilitates rapid experimentation and model development. The framework is implemented in both C++ and Python, and it supports acceleration on GPUs and TPUs, making it suitable for a wide range of computational tasks. PyTorch has emerged as a comprehensive solution for addressing various deep learning challenges [66].

IV.4.5 Kaggle

The model was implemented and trained on Kaggle, a web-based platform that is widely used to carry out machine learning and data science tasks. Kaggle provides an inbuilt Jupyter Notebook environment with Python and high-performance computing resources. For this project, the environment offered a GPU-accelerated session with two T4 GPUs, a session duration limit of 12 hours, up to 29 GiB of memory, and 15 GiB of GPU memory per GPU. The disk storage available reached up to 57.6 GiB. This setup enabled efficient experimentation, model training, and evaluation within a unified and accessible workspace.

IV.5 Experiments

IV.5.1 Dataset Overview

To evaluate and compare the models, we use the Food.com recipe dataset available on Kaggle [79]. This dataset includes 178264 recipes, 25076 users, and 1125284 collected ratings, covering the period from 2000 to 2018. Each recipe includes metadata such as a list of ingredients, cooking instructions, and detailed nutritional information (e.g., calories, fats, sugars, sodium, and proteins). User data includes explicit ratings (on a scale of 0 to 5) and accompanying textual reviews.

For this study, only features relevant to the recommendation framework were extracted:

- **User and recipe IDs** were encoded and embedded for collaborative filtering.
- **Ingredients** were tokenized and embedded to support content-aware recommendation.
- **Nutritional values** were used to compute a health score for each recipe.

To ensure data quality, we filtered the dataset to retain only users and recipes with at least 10 interactions. To reduce training time and computational complexity, we randomly sampled 100000 user–recipe interaction records from the filtered subset. The final dataset statistics are summarized in Table IV-1.

Table IV-1: A summary of the dataset used in this study.

Metric	Value
Number of Users	9016
Number of Recipes	12803
Number of Interactions	100000
Sparsity	99.9134%

IV.5.2 Data Preprocessing

Preprocessing is essential to transform the raw Food.com dataset into a structured format suitable for the hybrid NeuMF-based food recommendation system. The following steps were applied to encode collaborative and content-based signals while incorporating health-awareness into the model.

1. **User and Recipe ID Encoding** Users and recipes were filtered to retain only those with sufficient interaction history, reducing data sparsity and improving model generalization. Unique user and recipe IDs were mapped to integer indices and converted into embedding representations during training, forming the core of the collaborative filtering component.
2. **Ingredient Embedding Representation** Ingredients for each recipe were tokenized into individual units and mapped to unique indices to form an ingredient vocabulary. During training, the model retrieves embeddings for each ingredient and computes the average across all ingredients in a recipe. This aggregated embedding provides a fixed-length representation of ingredient content and is integrated into the MLP branch to enrich recommendations with content-based context.
3. **Health score** to encourage healthier food options, a Health score was calculated for each recipe based on seven important nutrients: proteins, carbohydrates, sugars, sodium, fats, saturated fats, and fibers. These nutrients were assessed in comparison to ideal ranges defined by the World Health Organization (WHO)[2]. These ideal nutritional thresholds are summarized in Table IV-2.

Table IV-2: Ideal ranges of nutrition [80].

Dietary factor	Ideal Range
Proteins	10-15%
Carbohydrates	55-75%
Sugars	<10%
Sodium	<5g
Fats	15-30%
Saturated fats	<10%
Calories	1800-2400 kcal

The score reflects how closely a recipe matches these nutritional standards.

The health score h_f for a recipe is defined as:

$$h_f = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}} \boldsymbol{I}(\boldsymbol{v_i} \in \boldsymbol{R_i})$$

2: https://www.who.int/health-topics/nutrition

Where:

- $\boldsymbol{N} = \boldsymbol{7}$ is the number of nutritional components,
- $\boldsymbol{v_i}$ is the value of nutrient $\boldsymbol{i}$ in the recipe,
- $\boldsymbol{R_i}$is the recommended range for nutrient $\boldsymbol{i}$,
- $\boldsymbol{I}(\boldsymbol{v_i} \in \boldsymbol{R_i})$ is the indicator function that returns 1 if $\boldsymbol{v_i}$ falls within $\boldsymbol{R_i}$, and 0 otherwise.

The final score $h_f \in [\mathbf{0}, \mathbf{1}]$. represents the proportion of nutrients within the recommended range, with higher values indicating better alignment with health guidelines.

IV.5.3 Evaluation Metrics

To evaluate the performance and compare the previously presented models, we used three commonly used evaluation metrics: Precision@k, Recall@k, and Normalized Discounted Cumulative Gain (NDCG@k).

- **Precision@k** measures relevant items within top-k recommendation sets.

$$\text{Precision@k} = \frac{Number\ of\ relevant\ items\ in\ top_k}{k}$$

- **Recall@k** measures the ability to retrieve relevant items in the top-k recommendations.

$$\text{Recall@k} = \frac{|\{Relevant\ items\} \cap \{Top_k recommended\ items\}|}{|\{Relevant\ items\}|}$$

  - | {Relevant items} |: denotes the total number of relevant items.
  - | {Relevant items} ∩ {Top-k recommended items} |: represents the count of relevant items included within the top-*k* recommendations.

- **Normalized Discounted Cumulative Gain (nDCG)** measures ranking quality considering the relevance of each item.

$$DCG_p = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{\log_2(i+1)}$$

  - Here rel_i denotes the relevance score of the item at position *i*, and *p* is the number of ranked items.
  - nDCG is calculated by dividing the DCG by the ideal DCG.

$$nDCG_p = \frac{DCG_p}{iDCG_p}$$

- (iDCG), which represents the DCG score of a perfectly ranked list.

IV.6 Results and Discussion

- **Post Filtering Model Results**

  The performance of the post-filtering approach was assessed by varying the α parameter in the final scoring function (defined earlier in Section IV.3.3). This parameter controls the balance between the NeuMF relevance score and the health score, enabling the system to prioritize recommendations based on either personalization or nutritional quality. The model's performance was assessed using Recall@10, Precision@10, and NDCG@10 metrics across several α values, with results summarized in Table IV-3

Table IV-3: Evaluation Metrics for the Post-filtering Model

Metric / Alpha	Recall@10	Precision@10	NDCG@10
0	**0.0003**	**0.0001**	**0.0003**
0.2	**0.0029**	**0.0010**	**0.0021**
0.5	**0.0088**	**0.0026**	**0.0052**
0.7	**0.0150**	**0.0039**	**0.0087**

The results indicate a clear positive correlation between increasing α and improved recommendation performance. When α = 0.0, the model depends exclusively on the health score, yielding extremely low Recall, Precision, and NDCG values demonstrating that healthiness alone is insufficient to capture user preferences. As α increases, the influence of NeuMF predictions becomes more prominent, resulting in marked improvements across all metrics. The highest performance is observed at α = 0.7, where Recall@10 reaches 0.0150 and NDCG@10 achieves 0.0087, indicating that prioritizing predicted user preferences while still incorporating health considerations yields the most balanced and effective recommendations. This suggests that, within the post-filtering paradigm, a moderate weighting of health alongside personalized relevance enhances overall recommendation quality.

- **Pre Filtering Model Results**

  The pre-filtering approach integrates health score directly into the model's input features during training, allowing the model to learn user preferences in alignment with nutritional factors. The results are summarized in table **IV-4.**

Table IV-4: Evaluation Metrics for the Pre-filtering Model

Metric	Value
Recall@10	**0.0142**
Precision@10	**0.0027**
NDCG@10	**0.0079**

These results indicate that the model is capable of recommending relevant and relatively healthier recipes while maintaining a reasonable level of personalization. The incorporation of health score as features contributes to a better understanding of user behavior in relation to nutrition, enabling the model to generate more balanced and meaningful recommendations.

- **Baseline Model Results**

  This model uses only user and recipe IDs, without incorporating nutritional or contextual information. It serves as a benchmark to measure the value added by the health-aware components in the pre-filtering and post-filtering models.

Table IV-5: Evaluation Metrics for the Baseline Model

Metric	Value
Recall@10	**0.0030**
Precision@10	**0.0006**
NDCG@10	**0.0015**

- **Comparison**

The evaluation across the three models: baseline, post-filtering, and pre-filtering, highlights the clear advantages of integrating content and health features into the recommendation system. The baseline model, which relies solely on user and recipe IDs, serves as a performance benchmark and illustrates the limitations of using only collaborative signals. Both the pre- and post-filtering models outperform this baseline by incorporating additional content-based and health-related information.

The post-filtering model offers flexibility by allowing health-aware adjustments after prediction through a tunable weighting factor α. When set to 0.7, this parameter achieves the best balance between personalization and health, leading to strong recommendation results. However, the model's overall effectiveness depends heavily on selecting an appropriate α value, which may require careful tuning and might not be straightforward in all scenarios.

Table IV-6: Performance Comparison of Baseline, Pre-filtering, and Post-filtering Models.

Metric / Model	Recall@10	Precision@10	NDCG@10
Baseline	**0.0003**	**0.0001**	**0.0003**
Pre-Filtering	**0.0142**	**0.0027**	**0.0021**
Post-filtering (α=0.7)	**0.0150**	**0.0039**	**0.0079**

IV.7 Conclusion

In conclusion, this chapter presented the design and implementation of a food recommendation framework based on the Neural Matrix Factorization (NeuMF) architecture. The framework combines collaborative filtering with content-based features to capture both user preferences and recipe characteristics. Two modeling approaches were developed: a pre-filtering approach, where health-related feature are incorporated during training, and a post-filtering approach, where health score are applied after generating recommendations. The chapter also outlined the model architecture, feature preprocessing steps, and evaluation methodology using metrics such as Precision, Recall, and NDCG.

General Conclusion

Recommender systems are among the most prominent applications of artificial intelligence in the modern era. They play a key role in providing personalized suggestions to users based on their preferences, past behaviors, and individual characteristics. These systems have become widely adopted across various sectors such as e-commerce, entertainment services, and education. However, their use in the food domain is beginning to gain traction, driven by growing public health concerns and the rising prevalence of chronic diseases such as obesity and diabetes.

In this context, Food Recommender Systems (FRS) have emerged as an innovative technological solution aimed at helping individuals choose recipes and foods that align with both their taste preferences and health needs. These systems rely on the integration of diverse data, including user dietary preferences, health conditions, available ingredients, and relevant nutritional information, such as nutrient values and caloric intake. FRS utilize a variety of techniques, including: Collaborative filtering, which is based on the similarity of behaviors or preferences between users; Content-based filtering, which focuses on the inherent characteristics of foods; And hybrid models, which combine both approaches. The advancement of machine learning and deep learning technologies has enhanced the accuracy of these systems and improved their ability to meet individual needs.

Despite these advancements, several challenges remain. These include the limited availability of accurate health data for users, and the difficulty of integrating health-related dimensions and personal preferences into a unified model. Therefore, it is crucial to strike an effective balance between user preferences and health requirements to ensure recommendations that are both personalized and reliable. To achieve this objective, we employed the NeuMF model to predict user preferences by integrating data on food ingredients, and a health score, in order to generate recommendations that align with user tastes while adhering to health standards. The NeuMF model was then reused this time without the health score based solely on ingredients. After the initial prediction was obtained, a linear function was applied to combine the model’s results with the health score, thus producing recommendations that balanced personal preferences with nutritional benefits.

It became clear that achieving this balance is a genuine challenge: an excessive focus on health aspects can lead to reduced user satisfaction or system effectiveness. As a result, a flexible and fair recommendation approach was adopted allowing for a reconciliation of personal desires with health requirements. This contributed to improved system performance and increased user satisfaction.

Future work aims to develop a more advanced approach capable of classifying users’ health status and providing food recommendations that integrate health dimensions without compromising the user experience. Promising directions include the integration of often-overlooked personal data, such as age, height, weight, gender, degree of food sensitivity, and physical activity level. Including these characteristics could enhance the precision of recommendations and their relevance to each user's specific situation. Furthermore, it is essential to consider cultural and social differences in eating habits when designing such systems, as these factors directly impact the effectiveness of the recommendations. Finally, the development of interpretable recommender systems based on the visual content of food and community preferences represents a promising area of research, potentially enhancing system transparency and user trust in the recommendations provided.

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