A Comprehensive Analysis of Machine Learning and Deep Learning Based Product Recommendation System

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Abstract. Recommender Systems (RS) have been widely applied in various real-time applications to support identifying valuable information. The RS tries to give actual suggestions to every user based on their behavior as well as interests. Recommendations generated by these systems often contend with the unique personal interests of individual users, thereby playing a pivotal role in their decision-making processes. Recommender Systems (RS) act as efficient tools for filtering vast amounts of online data, shaping the behaviors of smartphone users, personalization trends, and the evolution of internet access. RS are generally classified into three primary types: Hybrid Filtering, Content-Based Filtering (CBF), and Collaborative Filtering (CF). These systems find wide application across various fields including online education systems, e-commerce, marketing, tourism, food service, movies, business, and beyond. Although the recent RS are well-known in providing valuable recommendations, they suffer from a number of limitations as well as challenges such as scalability, sparsity, and cold-start and so on. Due to the various approach's existence, the selection of these approaches becomes challenging during the development of application-based RS. Moreover, every approach comes with its individual feature sets, advantages as well as limitations, which must be addressed. This survey reviews the research inclinations which integrates the progressive technical characteristics of the RS. The aim of this survey is to ensure a systematic review on recent contributions in RS domain, and concentrated on various applications such as education, food, products and so on. This survey provides a comprehensive review of these types of RS, recent literature, and applications of visual RS.

Keywords: Content based Filtering · Decision-making process · Hybrid Filtering · Collaborative Filtering and Recommendation Systems

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1 Introduction

The Recommendation Systems (RS) plays an important role in making suggestions for the products or items [1, 2]. The RS are utilized to filter the data from various networks and predicts the outcome according to the user's preference. The RS have enormously contributed to the meet the requirements of the users as well as promoting the sales by an advertisement on the social medias such as Amazon, Flipkart and so on [3, 4]. In recent times, recommendation systems have gained immense popularity, with the primary goal being to accurately recommend content to users based on a multitude of parameters. The RS can be widely utilized in various applications like, books, web, tourism, e-commerce, news, e-learning, music, entertainment, movies, food, hotel and so on [5, 6]. The recommendation system (RS) serves as a crucial tool in modern online platforms, aiding users in decision-making by suggesting relevant items, information, and services. In online stores, the primary objective is to recommend products aligned with user preferences to enhance the likelihood of purchase [7, 8]. These recommendations are often personalized based on factors such as customer demographics, product popularity, and past shopping behaviors [9, 10].

Despite considerable progress in RS technology, further advancements are necessary to deliver efficient recommendations across diverse applications [11, 12]. Various methodologies and algorithms are employed to build RS, typically categorized into three main types: hybrid filtering, Collaborative Filtering (CF), and Content-Based Filtering (CBF).

RS models frequently utilize graph-based hybrid methods, leveraging user information like demographics and location to improve recommendation accuracy [13, 14]. Among these methods, Collaborative Filtering (CF) is widely recognized, generating recommendations by identifying similar users or profiles. CF encompasses memory-based and model-based approaches [15, 16], with the former relying on similarity metrics and the latter employing Machine Learning (ML) techniques to construct user models [17, 18].

Conversely, CBF recommends items based on domain-specific information and user profiles. Hybrid filtering combines CBF and CF techniques to overcome individual limitations and enhance prediction accuracy [19, 20].

Ultimately, the goal of RS is to provide users with relevant recommendations tailored to their interests and preferences. The structure of the paper is organized into sections: Sect. 2 discusses RS types, Sect. 3 presents a literature analysis, Sect. 4 outlines inclusion/exclusion methodologies, Sect. 5 explores visual RS applications, and Sect. 6 concludes the survey with insights.

2 Types of Recommendation System

Recommender Systems (RS) are software tools and methodologies designed to suggest items that are of particular interest to users. These suggestions encompass various decision-making scenarios, including product purchases, movie selections, article readings, and more. RS vary in their approach to determining data sources and establishing similarities among users and items, which are then utilized to identify suitable matches.

The primary objective of recommendation systems (RS) is to provide customers with relevant products from a wide range of available options, tailored to their preferences. RS are generally categorized into three main types Hybrid RS, Content-based RS, and Collaborative RS. Figure 1 illustrates these RS types, and their systematic overview is detailed below.

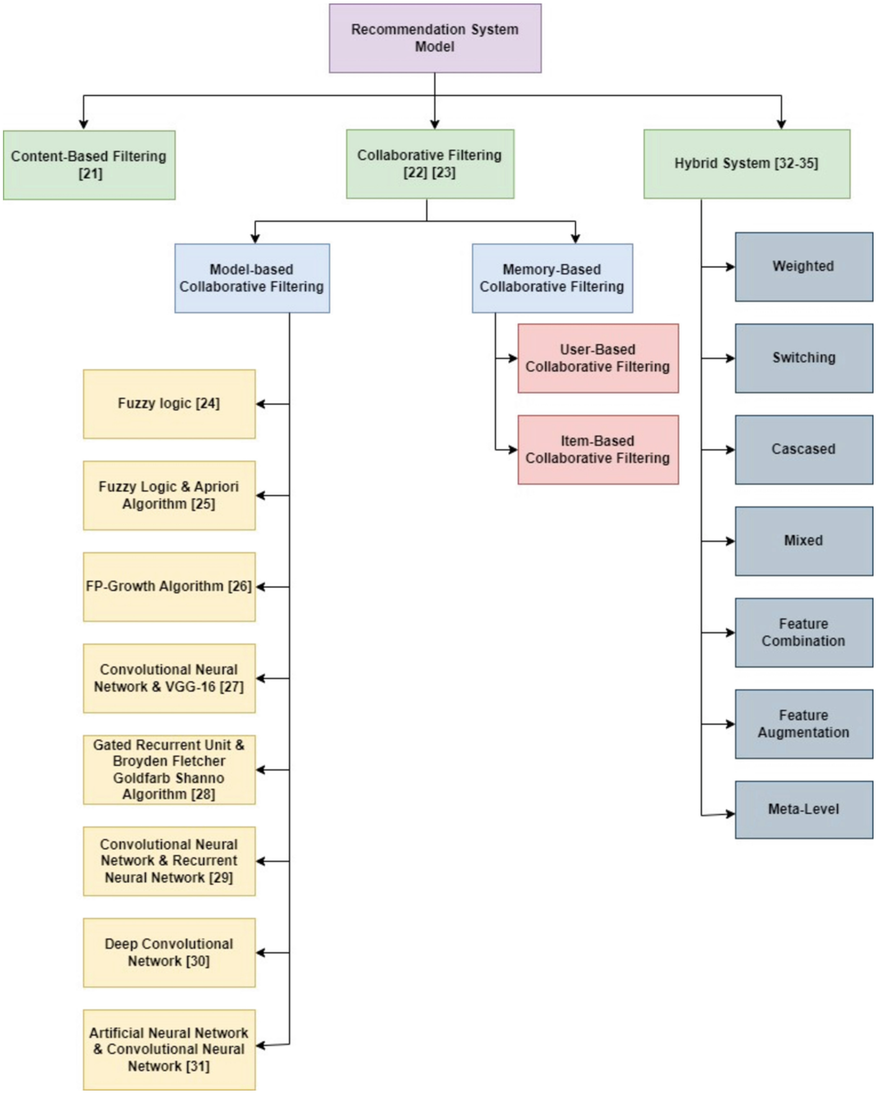

Fig. 1. Types of product RS

2.1 Content Based RS

The CBF is an approach for product recommendation with features similar to those the users prefer and recommends based on the product data. This is an approach of recommending similar product based on the product description which selected by the users in the past. CBF is the most general approach within the entire RS and it is widely utilized for early RS. The CBF approach suggest similar products according to the domain-specific conception of product information as well as user profile. The CBF approaches tries to recommend the products which is similar to those the consumer preferred in that past or is identifying in the present. Moreover, the CBF applies both sensing as well as analysis of the user content in order to give the personalized recommendations. The CBF concentrated on the regulations of particular consumers and products. It depends on the features of consumers as well as users rather than the product rating data of the user. Mario Casillo et al. [21] presented the Context-Aware RS based on embedded context idea. The approach has been thoroughly evaluated using diverse datasets to gauge its accuracy. Employing a range of datasets enables a comprehensive analysis of both the strengths and limitations inherent in the proposed approach.

2.2 Collaborative Based RS

The collaborative filtering (CF) is a data filtering approach which develops the preference database of the user using estimation data for the prediction of items that is suitable to the user interest. CF can be divided into two main types: Model-based and Memory-based. These models are described in detail below. Nattaporn Thongsri et al. [22] introduced a personalized healthy food Recommender System (RS) based on Collaborative Filtering (CF) combined with a knapsack approach. The experimental results showed that users were satisfied with the personalized healthy food RS utilizing CF, citing the system's capabilities, screen design, and efficiency as contributing factors. The presented approach utilized the users' details such as gender, height, weight as well as favorite food rating for RS. Then, these collected data are provided to the knapsack approach to recommend the menus which matched to the user's preferences.

2.2.1 Model Based RS

The model based RS are depending on the model creation out of the ratings dataset. On the other side, the model is developed using data extraction from the ratings dataset. This method has a latent to permit the most efficient solutions with respect to speed as well as scalability. Generally, model-based CF methods are in probabilistic or linear algebra-based approaches. There are various model-based approaches are described below.

2.2.1.1 Fuzzy Logic

R.V. Karthik and Sannasi Ganapathy [23] proposed a Fuzzy Logic-based Recommender System (RS) to dynamically predict the most relevant products for users in online shopping based on their interests. The Fuzzy Logic approach was developed to calculate the sentimental score of products within the user's target category. The introduced Fuzzy Logic rules and ontology-based RS approaches utilized ontology structuring for dynamic prediction of search content. The ontological dataset was designed to store domain data and facilitate decision-making through conceptual structuring. Results demonstrated that the introduced approach achieved superior performance compared to previous RS approaches in terms of accuracy in recommending relevant products for target users and the time taken to provide such recommendations.

2.2.1.2 Fuzzy Logic and Apriori Algorithm

The apriori algorithm is the traditional approach for learning association rules and it is utilized for the generation of item sets. The apriori approach is developed on the database, consisting of transactions such as the products bought the customers in the store.

Shu-Rong Yan et al. [24] presented the Internet of Things (IoT)-based smart purchasing system using apriori approach and fuzzy logic approach for the RS. In the presented approach, two significant pre-processing steps such as profile-reaction level as well as profile learning were employed to design the RS and after fuzzy logic and apriori algorithm is applied. Those pre-processing steps were measured the infrastructure of all RS. The presented approach performed the integration rules to represent the interdependencies as well as linkages between number of data objects. The integration rule was majorly utilized for identifying the "shopping cart analysis". As an outcome, the integrated rules were developed with the makes use of fuzzy logic and then apriori approach had selected the product based on the given fuzzy integration rules. Eventually, the suggested approach supported to enhance the diversity of the RS in IoT-based smart shopping.

2.2.1.3 FP-Growth Algorithm

Manal Loukili et al. [25] presented the Frequent Pattern-Growth (FP-Growth) algorithm for suggesting personal recommendations to the customer using integration rules. The presented approach had obtained the better performance with the maximum average probability of buying the next product suggested through the RS. For the identification of integration rules, the suggested approach utilized the FP-Growth approach which permitted from the history of transactions to identify the data. However, in this suggested approach, some of the estimation characteristics of the RS like explainability as well as diversity are complex to define.

2.2.1.4 Convolutional Neural Network and VGG-16

Akhilesh Kumar Sharma et al. [26] developed the Natural Language Processing (NLP) technique based efficient approach for the product RS. The developed approach utilized the Amazon Apparel dataset which involves 180000 samples for evaluating the performance of the developed approach. The NLP technique as well as CNN was utilized for the prediction of similar products. The CNN was utilized as final model to develop the feature vector from the product data and utilized this vector integrated with every vector for the prediction. The developed approach compared the distance among the vectors of all the products as well as recommend the recommend the products with minimum distance. The VGG-16 framework was utilized for the extraction of the features from the image. The CNN is the one of the Feedforward Neural Network (FNN) with the convolutional as well as pooling layers and which collects the global as well as local features. The CNN is efficient in processing the unstructured multimedia data for feature representation such as image, text, audio as well as video. The CNN is generally utilized on the outcome of the pre-processing step or time-frequency representation for modelling the user-item patterns and to collect higher-order correlations between embedding dimensions. A correlation matrix acquired through pairwise correlations, which enables the CNN layers to specify the better fully connected multilayer perceptron. This system forwarded the input to CNN for transitional time-frequency representation; hence it is capable to give recommendations even the lack of information for the new item. Figure 2 shows the architecture of CNN.

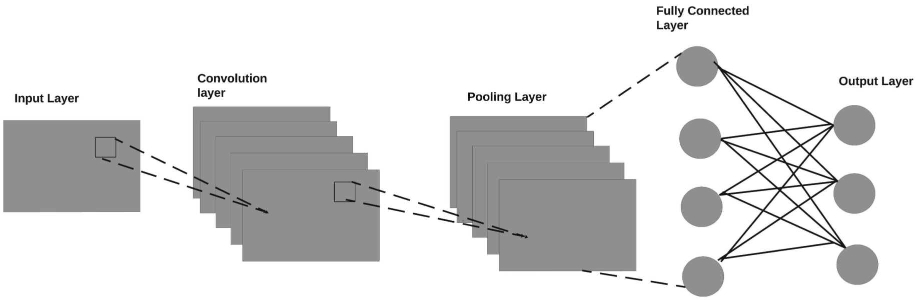

Fig. 2. Architecture of CNN

2.2.1.5 Gated Recurrent Unit and Broyden Fletcher Goldfarb Shanno Algorithm

A. Suresh and M. J. Carmel Mary Belinda [27] devised the GRU-BFGS (Gated Recurrent Unit based Broyden Fletcher Goldfarb Shanno) approach to enhance the predictive capability of the recommendation system (RS). Initially, they collected user views from Amazon user review databases and subjected them to preprocessing to extract essential information such as user ID, product ID, and ratings. They then employed matrix factorization and Non-Negative Matrix Factorization (NNMF) to construct the user-product interaction matrix, with the goal of minimizing the error between actual ratings and predicted product ratings. Additionally, they utilized GRU on the sparse interaction matrix to predict features and enhance the effectiveness of the implemented approach. Finally, the obtained matrix could be passed to the BFGS approach to recommend the most preferred products to users. Figure 3 illustrates the architecture of GRU.

2.2.1.6 Deep Neural Network

One type of Neural Network (NN) approach that incorporates a feedback loop is called Recurrent Neural Network (RNN). The RNN architecture comprises several layers, including input, hidden, output, and feedback links. Activation functions are used to integrate the connections between these layers. The network's output is re-input to the network through feedback connections. Chih-Han Chen et al. [28] implemented a personalized expert recommendation system (RS) for optimized nutrition, which directly filters and recommends personalized grocery products to consumers. The proposed approach introduced word embedding and padding techniques to convert textual data into generalized vectors, addressing various data types, unfamiliar grocery product names, and mitigating out-of-vocabulary issues. Deep Neural Network (DNN) is employed for product categorization, enabling handling of complex features and sequence logics of grocery product vectors. The decision recommendation approach was developed to take

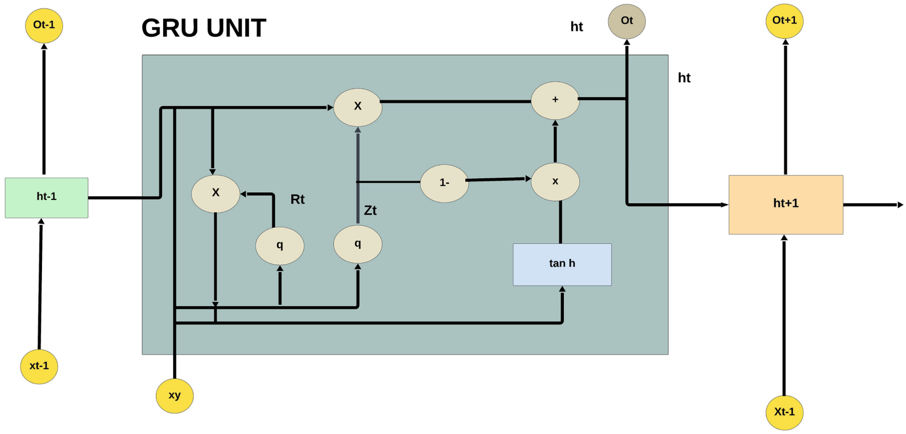

Fig. 3. General architecture of GRU

the categorization outcomes, and to evaluate the nutritional data. Furthermore, the introduced approach had utilized the Genetic Algorithm (GA) and the fitness score function for optimizing the suggestion given by the consumer. The categorized products were filtered based on an individual genetic data with combined phenotypic data. The scaling capability with unfamiliar data is utilized to attain the automatic categorization of the product. Unlike FNN, RNNs have loops and memories for remembering the former computations and it suitable to modelling the sequential data.

2.2.1.7 Deep Convolutional Network

Mehrdad Rostami et al. [29] introduced the Explainable Food Recommendation approach, which incorporates visual content of food to validate recommendations. They developed a new similarity score based on users' preferences for food categories, quantifying the extent to which a user community favors certain food types, and integrated it into the recommendation process. The proposed approach utilizes recommendations based on visual words extracted from a Deep Convolutional Network (DCN). In contrast to traditional food recommendation approaches, the visual words are typically obtained using bag-of-word techniques. The deep clustering-based DCN features are extracted with the aim of recommending the efficient recommendation services. Particularly, the suggested approach followed the three significant processes such as off-the-shelf feature extraction, development of the codebook as well as feature encoding. Eventually, the rule-based explain ability was developed to improve the transparency as well as interpretability of the recommendation results.

2.2.1.8 Artificial Neural Network and Convolutional Neural Network

Mehrdad Rostami et al. [30] implemented the hybrid food recommendation approach to address the problem in existing works such as cold start problem, time factors, eliminating the ingredients of the food, cold start users as well as community aspects. The suggested approach consists of two important stages such as content-based as well as user-based recommendation. In the initial stage, the graph clustering approach was utilized and in the second stage, the DL-based approach of Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) is used to group the food items as well users.

In addition, the holistic approach is performed to account for the user community as well as time related problems, in a way that enhances the recommendation quality provided to the user.

2.2.2 Memory Based RS

The memory-based CF (MB-CF) approach exploits the previous data which involves preferences and, in most situations, the ratings provided by the user to products are used to identify the similarities among user or items. As a result, the identified similarities are utilized to predict or determine the misplaced ratings for new products as well as provide recommendations to the users for the products which they previously unnoticed.

Generally, MB-CH approach begins by developing the user-item ratings matrix according to pervious ratings. Every row of the matrix involves the ratings provided by user to every product. Hence in the matrix, every row or column resembles to particular user or item. In that every element r_{uj} of the matrix denotes ratings given of the user u for the item j. In that, the matrix involves ratings given by the user for products. For RS, the MB-CF approach initially tried to predict the misplaced values associated with a target user or candidate item, after recommending the products with the maximum ratings.

To predict the ratings such as missing matrix value, the MB-CG approach initially tries to identify the relationships among the user and item through applying the similarity function. The closely related target users and products are also known as neighbors of the target user, hence this case, the MB-CF approach is called the neighborhood-based CF approach. Subsequently, the ratings provided the neighbors are utilized for the prediction of the missing matrix values. The memory based model can be divided into two types such as User-based and Item-based RS.

2.2.2.1 User based RS

The user based RS approach initially utilizes the similarity function among the rows of the rating matrices, for predicting the neighbor user of the target user. Afterwards, the prediction of misplaced ratings for some item provided through target user consists of weighted average computation (based on the similarity among every neighbor as well as target user) ratings.

2.2.2.2 Item based RS

An item based RS approach initially utilizes the similarity function among the columns of the rating matrices for identifying the neighbor products of the user product. Later, the MB-CF approach utilizes the ratings provided by the user to these products for the prediction of user preference of the product.

2.2.2.3 Hybrid MB-CF

Eventually, the hybrid MB-CF approach integrates the similarities estimated from user-based as well as item-based RS approach for the enhancement of the prediction accuracy.

2.3 Hybrid RS

The Content-Based Filtering (CBF) and Collaborative Filtering (CF) approaches each have their limitations: CBF relies on item metadata preferred by users, while CF depends on user rating data. To overcome these limitations and improve recommendation performance, hybrid RS approaches have been developed. These hybrid RS approaches are categorized into various types such as weighted, cascade, mixed, feature-combination, feature-augmentation, switching, and feature-augmentation.

Bogdan Walek and Per Fajmon [31] introduced the Eshop recommender, a hybrid RS integrating three subsystems: CBF, CF, and fuzzy expert systems. This approach recommends products based on user interests and activities on the Eshop, utilizing a fuzzy expert system.

Yassine Afoudi et al. [32] implemented a robust recommendation approach based on CBF, CF with self-organizing map, and content-based model. Integrating Self-organizing map with CF minimized RMSE in the majority of clusters compared to K-means clustering with CF, leading to the development of an efficient hybrid system.

S. Bhaskaran and Raja Marappan [15] devised a generalized modeling approach integrating enhanced clustering and trust-based Support Vector Machine (SVM) to achieve hybrid and personalized recommendations for e-learners. Learner performance is estimated based on their habits and interests, analyzing confidence levels to provide improved recommendations.

On the other hand, Pratik K. Biswas [33] developed a hybrid Recommender System (RS) combining Alternating Least Squares (ALS) based Collaborative Filtering (CF) with a Deep Learning (DL) approach. This approach aims to enhance recommendation performance and address CF limitations, particularly the cold start problem. It integrates outcomes from ALS to influence recommendations from a Deep Neural Network (DNN), utilizing various data types to recommend smartphones to prospective customers effectively.

3 Literature Review

The realm of recommendation systems (RS) has attracted considerable attention owing to its potential advantages, including scalability, customer loyalty enhancement, and reduced advertising costs. This section provides an overview of current research in the field, categorized into RS based on Machine Learning (ML) and RS-based on Deep Learning (DL).

Aditya G M et al. [34] introduced a real-time food RS aimed at streamlining user experiences in food ordering systems. By leveraging a mobile application developed with Flutter and powered by ML, this system recommends menus to users based on their past orders, thereby digitizing and scaling up food ordering operations.

N Pavitha et al. [35] explored supervised ML methods, such as Naïve Bayes (NB) and Support Vector Machine (SVM), for movie recommendation classification and sentiment analysis. Their approach employs the Cosine Similarity model for suggesting similar movies and integrates sentiment analysis to enhance user satisfaction.

GM Harshvardhan et al. [36] presented the Unsupervised Boltzmann Machine-based Time-aware RS (UBMTR) for recommending visual media. Utilizing Restricted Boltzmann Machines (RBM), UBMTR detects hidden features in user ratings and time data, effectively addressing challenges related to missing values and imbalanced datasets.

Yejing Wang et al. [37] developed an Auto ML framework to adaptively select features in a DL-based RS, improving system efficiency, flexibility, and scalability. However, the model's reliability may be compromised due to inadequate training data.

Zeinab Shahbazi and Yung-Cheol Byun [38] proposed a virtual and intelligent-based RS using Natural Language Processing (NLP) and ML to recommend e-learning course selections. While their approach efficiently learns and identifies learner characteristics through clustering, it lacks theoretical validation of its reasoning.

Juan Carlos Cepeda-Pacheco and Mari Carmen Domingo [39] devised an IoT-enabled DL-based RS for recommending tourist attractions in smart cities, mitigating the cold start issue by incorporating personal data into a Deep Neural Network (DNN). Nonetheless, RS state and action spaces may face challenges due to dimensionality.

Hyeon-woo An and Nammee Moon [40] introduced a hybrid CNN and LSTM-based sentiment analysis for tourist spot RS, enabling tailored recommendations based on contextual factors and weather data. However, extensive processing is required, impacting system efficiency.

Zahra Zamanzadeh Darban and Mohammad Hadi Valipour [41] presented a Graph-based Hybrid RS (GHRS) for movie recommendations, combining user rating similarity and demographic data. While GHRS offers superior recommendation accuracy, it may experience temporary service disruptions and reduced operational speeds.

Sandipan Sahu et al. [42] introduced a DL approach using CNN and a new feature set for multi-class movie popularity prediction. This approach utilized movie features and review data to predict movie popularity among different audience groups, although it required high computational power and training time.

Sasmita Subhadarsinee Choudhury et al. [43] proposed an implicit trust value and various ML approaches for movie recommendations to trusted users, combining user similarity with weighted trust propagation. While Back-propagation Neural Network (BPNN) did not require prior network knowledge, the approach may not capture complex data relations due to its linear model.

3.1 Comparative Analysis

The comparison of product RS estimation with existing models is vital for improving model performance effectively. The analysis presents insights into several performance metrics, including accuracy, F1-score, precision, Mean Square Error (MSE), Normalized MAPE (NMAPE), Root Mean Square Error (RMSE), recall, Area Under Curve (AUC), Mean Absolute Percentage Error (MAPE), diversity, and time. Below is a summary of the comparative analysis from Table 1, outlining the strengths and weaknesses of each method.

4 Methodology

The resolution of this survey is to determine the research tendencies in the area of RS. The research nature in RS is complex to restraining every paper to a particular discipline. This can be further unstated by the circumstance that the articles on RS are dispersed over number of journals such as Information technology, marketing, information science and so on. Therefore, this survey utilized the papers over the greater number of journals as well as research databases such as Google scholar, IEEE Xplore, Springer, Research gate, Science direct and so on. The research process of the RS based articles are taken by using various keywords such as "Recommendation Systems", "Types of Recommendation Systems", "Content-based filtering", "Collaborative filtering", "Hybrid" and so on.

This survey has screened the total of 150 research articles based on their abstracts as well as their contents. However, some unrelated articles, ineligible records, not-retrieved

Table 1. Comparative analysis of the existing methods

Author	Methodology	Advantages	Limitations	Performance Criteria
N Pavitha et al. [35]	Naïve Bayes and Support Vector Machine based movie recommendation and sentiment analysis	The approach increasing the efficiency of the RS by minimizing computational overload	The SVM was not suitable for the large datasets and it does not perform well when the dataset had more noise	Accuracy = 0.9863, Precision = 0.98278, Recall 0.9937, AUC = 0.984
GM Harshvardhan et al. [36]	An unsupervised Boltzmann machine-based time-aware recommendation system (UBMTR) for the detection of underlying hidden features in user-movie ratings data	The UBMTR had greater prediction effectiveness as well as better inference efficiency	Training UBMTR approach had computationally expensive, particularly for the large datasets. The learning process can sometimes obtain trapped in local minima which leads to sub-optimal solutions. Moreover, complex to interpret the features learned through RBM	MSE = 0.76, RMSE = 0.88, MAPE = 0.414, MAE = 0.76, NMAE = 0.76, NMAPE = 0.414
Yejing Wang et al. [37]	AutoML framework based significant feature selection in an automatic manner for the deep RS	AutoML supports deomcratize ML by permitting non-trained users to utilize ML tools and technologies	the suggested approach had produced the unreliable predictions due to the insufficient training data	AUC = 0.7773, Log loss = 0.3813, Time = 10.98% saved in IPNN

(*continued*)

Table 1. (*continued*)

Author	Methodology	Advantages	Limitations	Performance Criteria
Zeinab Shahbazi and Yung-Cheol Byun [38]	Natural Language Processing (NLP) as well as semantic analysis approaches for the course selection recommendation to the e-learners as well as staffs	Repetitive tasks like collating investigations or processing forms are done with more accuracy	The presented approach had only focused on the user's demand as well as not provided the theoretical proof of the rationality reasoning	Degree of diversity = 0.44, 0.36 and 0.39 in SI-IFL for content, media and difficulty Mean time = 115 min MAE = 0.43 and 0.45 for agent-based and collaborative filtering
Juan Carlos Cepeda-Pacheco and Mari Carmen Domingo [39]	IoT-enabled Deep Learning (DL)-based RS for enhancing the tourist experience in smart city	This model is most suitable for large scale datasets	The state as well as action spaces in RS frequently suffered from the dimensionality curse	Accuracy = 0.997, Precision = 0.999, Recall = 0.999, F1-score = 0.998, Loss = 0.005
Hyeon-woo An and Nammee Moon [40]	Hybrid method of CNN as well as Long Short-term Memory (LSTM) approach-based sentiment analysis for the tourist's spot RS	The suggested approach has less susceptible to the vanishing gradient problem	There was still large amount of integrated-column sending process was needed	N/A

(*continued*)

reports are removed. Eventually, 50 suitable articles are chosen from the higher journals and in recent years' papers. Figure 4 shows the flowchart for this survey.

Table 1. (*continued*)

Author	Methodology	Advantages	Limitations	Performance Criteria
Zahra Zamanzadeh Darban and Mohammad Hadi Valipour [41]	Graph-based Hybrid RS (GHRS) for movie recommendation	Hybrid Recommender Systems can provide more accurate recommendations by combining the strengths of different recommender systems	The suggested approach had inevitable that may result in temporary service interruption as well as decreased the operational speed	Precision = 0.792, Recall = 0.838, RMSE = 0.833
Sandipan Sahu et al. [42]	Convolutional Neural Network (CNN) and new feature set for multi-class movie popularity prediction	CNN had the capability to handle the large datasets	CNN had required the high computational power as well as long time to train the model	Accuracy = 0.968, Precision = 0.96, Recall = 0.96, F1-score = 0.96 Similarity distance = 1.5076
Sasmita Subhadarsinee Choudhury et al. [43]	Backpropagation Neural Network (BPNN), Singular Value Decomposition (SVD), DNN as well as DNN with Trust are compared to recommend the appropriate movie to the user	The BPNN had not required the prior knowledge about the network	However, the suggested approach had not collected the complex relation in data due to the linear model	MSE = 0.748 Accuracy = 83%

5 Applications of Visual Recommendation System

The RS has been significantly extended as well as utilized in various applications. This survey projected to analyze how the recommendation approaches as well as technologies for previously described various RS are studies. Figure 5 shows the various applications based on RS.

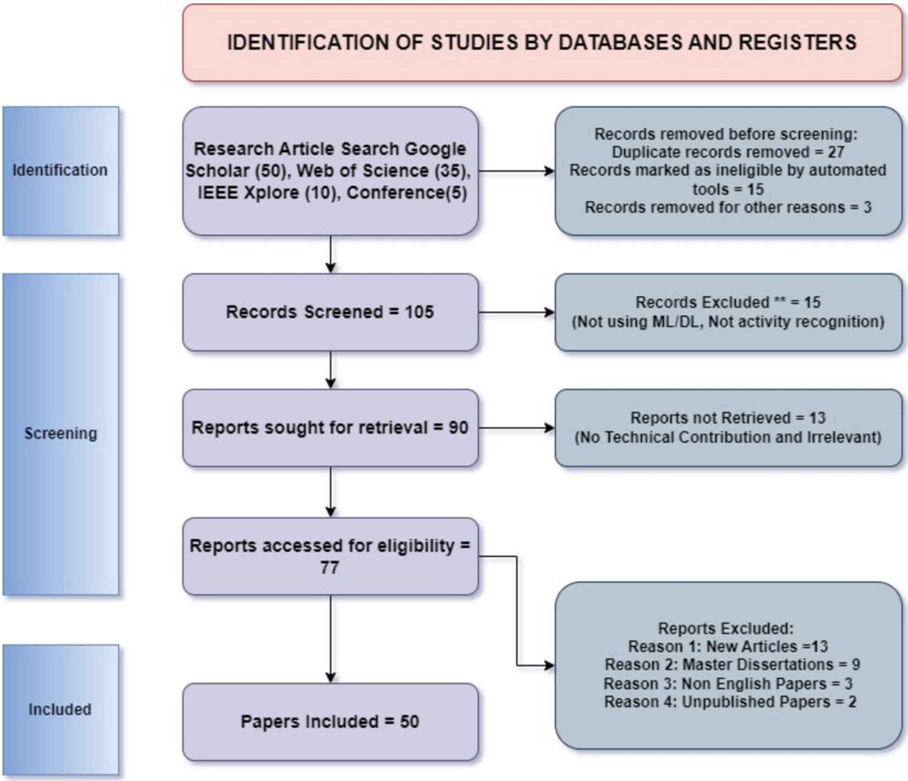

Fig. 4. Flowchart of the inclusion and exclusion process for RS

5.1 Tourism

The research on RS using Social Network Service (SNS) has enhanced in the field of tourism. As the demand for the travel is enhanced, the RS have been commenced to utilize in tourism area to recommend the termini, routes as well as transportation. The travel-related RS utilizes the situational data like review data, location of the user, time, weather and so on, these can be collected by the SNS. It can store the check-in data of the user as well as post uploaded location through user. The travel RS determines the SNS data as well as supplies the travel data appropriate to the user's interest, thus enhancing the satisfaction of the user as well as enhances the faithfulness in tourism.

Khalid AL Fararni et al. [44] presented the various RS approaches which had been utilized in the field of tourism. The hybrid recommendation approach was developed based on the architectural as well as conceptual framework for the tourism RS. The presented approach goes beyond the recommendation of the tourist attraction list as well as tailored to the tourist interest. In that, the presented architecture was decomposed into five main modules such as visitors' profiles, service repository, contextual meta-model, hybrid filtering process as well as trip planner.

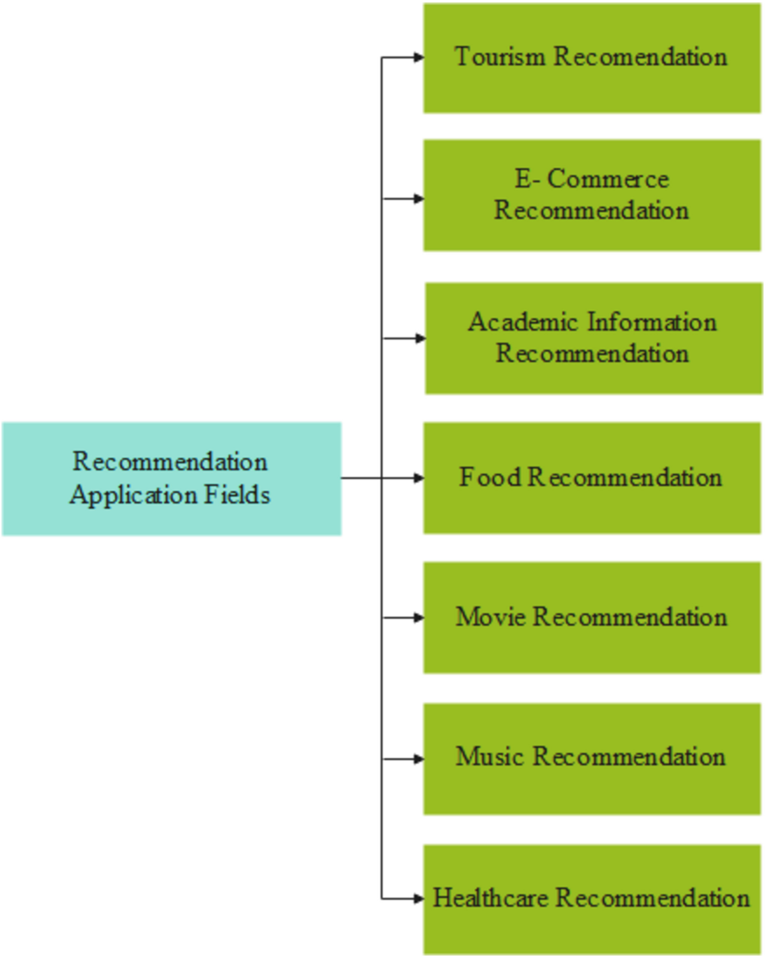

Fig. 5. Applications of Recommendation System

5.2 E-commerce

The E-commerce contributes the users as number of items as well as choices in an online environment, and it supplies the sellers with a simple to sell the product. E-commerce collects the information related to the number of users for business expansion as well as significantly utilizes these data in RS. This service predicts the user preference through determining the auxiliary user data like age and gender. The product findings similar to the products previously purchased through the user is supportive for recommending the products which is liked for the user.

Aleksandra Baczkiewicz et al. [45] implemented an innovative model that incorporates Multi-Criteria Decision-Making (MCDM) approaches as a vital component of a user Decision Support System (DSS) for recommending suitable products from a given set of alternatives. The DSS provides dependable recommendations to consumers within a compromise ranking range derived from various MCDM approaches. The methodologies encompass Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) with Characteristic Objects Method (COMET), Combined Compromise Solution (COCOSO), Evaluation based on Distance from Average Solution (EDAS), MAIRCA, and Multi-Attribute Boundary Approximation Area Comparison (MABAC). Each of these approaches contributes to the final ranking development using Copeland land.

5.3 Academic Information

Due to an exponential enhancement of academic data, researchers spend their crucial time as well as effort to identify the academic data

In academic data applications, research on recommendation systems has been conducted to provide scholars with useful data and technologies for their research endeavors. Specifically, in University Digital Libraries (UDL), these services support university learning, research, and education. Recommendation systems are utilized not only for accessing academic data but also for tasks such as writing articles and facilitating the submission process for researchers. The aim of recommendation systems in academic services is to suggest and deliver academic data that caters to a diverse range of researchers, including research institutions, development practitioners, scientific communities, and beyond.

Sadia Ali et al. [46] presented the E-learning Recommendation Architecture (ELRA) for the semantic recommendation with the help of virtual agents according to the requirements as well as preferences of the user. The user preferences are depending on the semantic analysis of the user's request which followed through the hybrid recommendation system for course recommendations. As an outcome, the ELRA approach was categorized into two parts: the first part was utilized for the extraction of input data and represents it as the list of suggestions. Then, another part was utilized feedback to perform the recommendation process to develop helpful recommendations. The performance of the ELRA approach was determined with the help of quantitative model. Consequently, the virtualized agent-based recommendation system not only improves user learning skills but also streamlines course selection based on the user's preferences and interests.

5.4 Food Recommendation

Food recommendation presents an intriguing challenge, offering users guidance in their food choices tailored to their specific preferences. Such systems are seen as efficient tools for aiding users in altering their eating habits to achieve a healthier diet.

N. C. Brintha et al. [47] developed three distinct systems: a diabetes prediction system, a food recognition system, and a food tracking system. The diabetes prediction system utilizes Artificial Neural Networks (ANN) to forecast diabetes based on user-input values such as glucose level, blood pressure, skin thickness, age, and insulin levels. For food recognition, Convolutional Neural Networks (CNN) are employed in conjunction with nutrient information. Additionally, transfer learning-based VGG-16 is utilized for daily food tracking. This comprehensive system empowers users to effectively monitor their food intake. Upon predicting diabetes, the system can upload an image to identify the food and provide nutritional details and calorie values.

5.5 Movie Recommendation

The video content like movies is extremely consumed by the users using TV, theaters, mobile phones and so on. The significant content of video content is utilized by the streaming platforms like You Tube as well as Netflix. The audio is also change from download as well as consume files to the user's local device to consume the data by streaming platforms like YouTube music and Tidal. The streaming services related to the media content have been developed along with the RS, because it is required to minimize the user's uncertainties about selecting the large number of content as well as to provide the content which is personalized to every user.

Hossein Tahmasebi et al. [48] developed the hybrid social RS based on Deep Autoencoder Network (DAN) for the movie recommendation. The DAN implemented a hybrid approach combining Collaborative Filtering (CF) and Content-Based Filtering (CBF) to account for the social influence of the user. The social influence of every user was estimated according to the user social characteristics as well as behavior on the Facebook or Twitter. The movie properties have been utilized by CBF for solving a cold-start problem. Afterwards, the ratings have been predicted for the movies by using CF as well as DAN.

In a Deep Averaging Network (DAN), the input data undergoes transformation within the output layer, with a bottleneck layer utilized to encapsulate the features of the input data. For the experimentation, the Movie Tweeting's as well as Open Movie datasets were collected to estimate the DAN approach.

5.6 Music Recommendation

The Social Network Service (SNS) like Twitter, Facebook, YouTube and so on are the enormous digital-based social exchanges. The massive enhancement in the utilization of SNS is established through the enormous enhancement in user-related information. It is suitable to collect the content data that the user can registered with the post by SNS. Moreover, the ratings, feedback, likes and comments data can be collected to estimate the user interest. The obtained data are not only used for the recommendation within SNS, but also access to useful for the other business recommendation.

Xinglin Wen [49] developed the DL approach of Faster-RCNN for the extraction of underlying features of the scene data. A sophisticated background music system was created by harnessing Faster R-CNN and Internet of Things (IoT) technology, enabling multi-scale feature extraction. This innovative system utilizes a middle-level feature framework to extract crucial features from scene data. Additionally, it delineates the fundamental functional elements of the intelligent background music system. The developed approach had showed the encouraging results in data processing for the communication approaches. However, the developed feature extraction approach based on DL is an optimal effect. The advantage of the developed intelligent background music system approach is stable and effective.

5.7 Healthcare Service

Smart devices gather extensive biometric data from users to aid in disease-related research by analyzing body conditions. Health-related recommendation systems analyze the correlation between symptom patterns and diseases in patients, providing users with insights for making better treatment decisions. In this survey, the RS is divided into two types such as health RS field as well as e-health field, which supports to professional treatment based on the system application. Within the realm of health recommendation systems, the primary goal is to provide enhanced treatment approaches customized to the symptoms of various diseases and their corresponding stages. Ultimately, these systems gather data on both the patient and the characteristics of the disease to achieve this goal.

6 Challenges

This section shows the challenges played through the RS process and Fig. 6 shows the various challenges in RS.

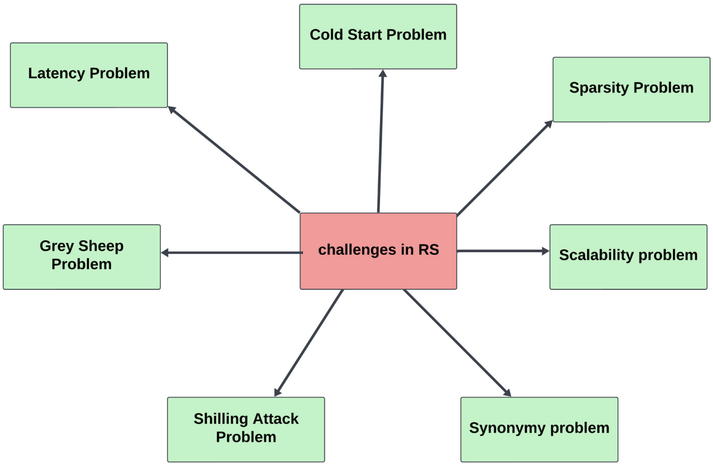

Fig. 6. Challenges in product RS

6.1 The Cold Start Problem

When new users or items are introduced into the system, it presents a challenge. This issue manifests in various forms, including the introduction of new users, new items, and adjustments to the system itself.

Several researchers have addressed the cold-start problem through using older technique of content based algorithms or newer hybrid methods which are combination of content based and collaborative approaches. Through presenting more popular goods and collections of the data about their users, an app can become a powerful tool for understanding features of thoroughly tested and approved products better. Machine learning handles signals like clicking feedback and implicit signals, and social network data impacts in two aspects: the relevance and the trustworthiness of recommendations.

6.2 The Sparsity Problem

This is encountered by the CF approach, where the data sparsity has great impact on given recommendation's quality. An important reason behind this problem is that, the user only rates the minimal subset for the products. CF approaches are suffered from the data sparsity problem, since it majorly depends on the rating matrixes to develop suitable recommendations. In CF, the over specialization problem ignores the user from identifying the new products or other existing options. This states that, the users are constrained to the recommendations which directly related to the user profiles.

Authors tried to explain the problem of sparsity through matrix factorization, collaborative filtering and hybrid methods. These methods ascertains trends that hitherto were not obvious in otherwise thin data and they also help with avoiding the popular dependence on user-item interactions

6.3 The Scalability Problem

The scalability estimated the system capability to work with the greater performance even when the availability of maximum data. In CF based RS, exponential computation overheads development leads to provide the inaccurate outcomes.

Scalability is a key factor in recommendation systems, due to the usage of distributed computing solutions like Apache Spark, caching, as well as servers under micro services and cloud computing. These techniques expect data processing might be shorter and computation time reduced so that they can be scaled up easily

6.4 The Synonymy Problem

This occurs when a product is characterized into two or more names or registrations with similar meaning. In this situation, CF based RS cannot determine whether the denoted terms are same or different.

6.5 The shilling Attack Problem

This occurs when the malicious user enters into the system to provide the ratings for the fake item. This condition happens when the malicious user needs to either maximize or minimize the popularity of the item by causing the bias on the selected target products. The shilling attacks significantly minimized the system consistency.

6.6 The Latency Problem

The challenge arises in collaborative filtering (CF) approaches when new items are frequently added to the database, leading to the system's inability to recommend these novel products effectively. While CF can address latency issues associated with recommending new items, it can also result in overspecialization and diminish computing efficiency and overall system performance.

6.7 The Grey Sheep Problem

This scenario pertains to the CF approach, wherein feedback from a user does not align with any similar users in the system's neighbourhood. Consequently, the system struggles to predict suitable products for that user.

7 Conclusion

The development of an internet and smart devices have leads to an expansion of many applications and web services. Hence, it is necessary to introduce the various RS which can supports user to preciously obtain an item information as well as decision-making. Thus, the RS for various application that influence the real-time data obtained through the wearable devices, Personnel Computer (PC) and so on. The RSs have attracted the consideration of number of researchers as well as academics. In this survey, types of RS, literature survey, applications of RS and challenges are discussed. Initially, the types of RS have been discussed such as CBF, CF and Hybrid based RS. After that, the existing researchers followed by a sequential review of the many existing RS are discussed. The various applications of the RS have been analyzed such as tourism, healthcare, education, academia, movie, music, food and e-commerce. There is a significant scope of research is utilizing the Neural Network (NN) as well as DL-based approaches for developing the RS. The systems developed using these approaches are identified to obtain the greater performance. In future, will plan to develop the survey to research and development of the RS appropriate for the business features through the application service area.

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