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Research Issues, Innovation and Associated Approaches for Recommendation on Social Networks

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Abstract

Recommendation Systems have been well established to reduce the problem of information overload and have become one of the most valuable tools applicable to different domains like computer science, mathematics, psychology etc. Despite its popularity and successful deployment in different commercial environments, this area is still exploratory due to the rapid development of social media which has accelerated the development of social recommendation systems. This paper addresses the key motivation for social media sites to apply recommendation techniques, unique properties of social recommendation systems, classification of social recommendation systems on the basis of basic models, comparison with existing traditional recommender systems, key findings from positive and negative experiences in applying social recommendation systems. Consequently, the aim of this paper is to provide research directions to improve the capability of social recommendation systems including the heterogeneous nature of social networks, understanding the role of negative relations, cold-start problems, integrating the cross-domain data and its applicability to a broader range of applications. This study will help the researchers and academicians in planning future social recommendation studies for designing a unified and coherent social recommendation system.

Keywords: cold-start; collaborative filtering; negative relations; social network; social tagging; sparsity; trust; user modelling

1. Introduction

Recommender systems are information filtering systems that deal with the problem of information overload [1] by filtering vital information fragment out of a large amount of dynamically generated information according to user's preferences, interest, or observed behavior about item [2]. Recommender Systems are defined as a decision making strategy for users under complex information environments [3]. As the number of choices on the web is increasing, there is a need to filter and efficiently extract the relevant information to timely access the items and meet the user's needs; this causes the demand for recommendation systems to increase a lot. Recommendation systems are beneficial to both online retailers in terms of revenue and users in selecting the most relevant products. [4]. Recommendation systems are relevant to numerous domains such as movies, books, products, music, videos, blogs, news, friends, and many more [1, 5-9]. Due to its applicability in numerous domains, it is still an active area of research that helps users to deal with information overload problem by automatically generating personalized recommendations that fit the user's interests. For instance, if a user wishes to buy a mobile phone, then it would be cumbersome to go through all available online reviews; this task is automated by recommendation systems by suggesting items as per users' interests.

Despite its advancements, current recommendation systems still require further refinements to make recommendation techniques applicable to a wider range of domains related to real life applications. The major drawback of traditional recommendation systems is sparsity. When the number of reviews for a particular item is less, then it becomes difficult to suggest. Cold-start issue is when a user is new to the system, then similar users can't be established. Uncertainty in taking decisions in such an open-ended network as users are not connected [1,10,11]. Thus, refinements should include more advanced recommendation methods, incorporating users and items information [12,13]; emphasis should be given to implicit feedback in addition to explicit feedback [14], usage of multi-criteria ratings [15,16], incorporating social correlation, and acquiring knowledge of multiple domains [17,18]. The extension of these capabilities and embedding of social layer in existing recommendation systems helps in increasing the efficiency and hence the performance of current generation recommendation systems.

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In today's digital world, people are more inclined towards social networks, thus integration of social networks into the traditional recommendation techniques like collaborative filtering, content-based and hybrid approach enhances the performance of recommendation systems [19-21]. People often share their personal choices with their friends or within their social circles; thus, people also rely more on suggestions specified by their friends as compared to some unknown persons [22]. For instance, before taking a decision to watch a movie, a user often asks within their social circle if it is worth watching a movie as social bindings play a major role in affecting the decisions of users. Thus, social networks provide new room and opportunities to improve the accuracy of existing recommendation systems.

The major goal of this survey is to provide a comprehensive review of the research efforts and advancements accomplished in the domain of social network based recommendation systems. It provides an overview and analysis of social recommendation scenarios that involve additional information about user-item interaction beyond user-item matrix like social interest, social trust, and social influence among users in a social recommendation system as additional inputs [22-24]. This embedding of social parameters augments the bond on social platforms and generates more peculiar and reliable suggestions for users towards different services. This survey can be laid down as a foundation for the researchers and academicians that are interested to innovate and explore further in this domain. The contribution of this survey is four-fold: (i) theoretical key concepts and classification of social recommendation approaches that have been developed in literature are described to properly formulate the current work (ii) few popular publicly available datasets are listed at one place that eases the task of researchers (iii) research challenges are outlined that contributes in the initiation of new ideas to explore further in this domain (iv) future research directions are discussed that expands the horizon of the research work in this field.

The rest of the survey is organized as follows: section 2 describes the key concepts, social recommendation taxonomy, and a few popular datasets, section 3 outlines the research challenges confronted, and section 4 discuss the future research directions and extensions that can be explored further and section 5 concludes this research study.

2. Overview of Social Recommendation Systems

The tremendous growth and popularity of social networks have made users more prone to such platforms and thus people get persuaded due to relationships formed on social networks [25]. On the other hand, traditional recommendation systems suggest products solely based on the rating criterion but the major issues with such systems are sparsity-number of ratings are few in the database, as not all users wish to submit the feedback regarding products; cold-start issue-when a user is new to the system, then it becomes difficult to find similar users; lack of trust- people trust strangers' decision less as compared to known people. Thus, recommendation systems should take into consideration formed social relationships, social influence, social trust and other such factors in the current generation of recommendation systems [22-24]. This has evolved the development of social recommendation systems.

2.1. Definition of Social Recommendation Systems

Social recommendation systems are defined as information filtering systems that take an additional input in the form of social relationships, social influence, and social trust [26]. In contrast, traditional recommendation systems take rating as an input, as shown in Table 1 and Figure 1. Table 1 depicts the traditional recommendation systems wherein users submit multiple ratings towards different items, but in these systems, users are independent of each other.

Table 1. User-item rating matrix in traditional recommendation systems

Users/Items	**I1**	**I2**	**I3**
U1	5	3	?
U2	1	?	4
U3	2	?	?
U4	3	2	5
U5	3	4	4
U6	5	3	?

Figure 1. depicts users connected in a social network and Table 2 illustrates the social recommendation systems scenario where users submit multiple ratings towards different items. In these systems, users are connected to each other in a social network.

Table 2. User item rating matrix in social recommendation systems

Users/Items	I1	I2	I3	I4
U1	5	?	3	?
U2	?	?	?	?
U3	5	?	3	1
U4	?	?	?	3
U5	?	?	?	?
U6	?	2	?	?

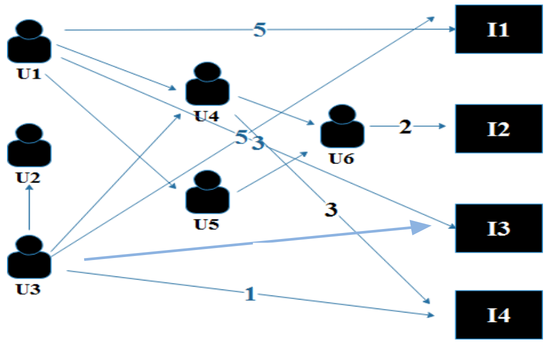

Figure 1. Social network

2.2. Why Social Network Recommendation Systems Research?

In recent years, the tremendous growth of social activities like social posts, tweets, likes, dislikes, membership, following up, retweets, tagging on social platforms like Facebook, Twitter, Instagram has originated an enormous content [25,26] that has become a challenge for users to extract the most relevant information within short time-span. This has motivated researchers to develop unique and efficient algorithms for social platforms that can ease the decision of users in choosing the correct service/products. It is observed that researchers have innovated and implemented new ideas in the past few years [22-24,27-29] and is still an active area of exploration due to the dynamic nature of the structure of the network. Before, moving into the details of social recommendation systems approaches, it is essential to know the basic factors that affect the recommendations generated in a social network [26] as listed below:

a) *Social Influence:* The users get influenced by those users with whom the strength of bond is more that is close friends' decision impacts higher than others like U1 and U4 users connected in a network are close friends as shown in Figure 1. The social information including the users' interests and friends connected in a network is appropriated in He et al. work [30] interpreted that the utilization of social information gives more reliable recommendations. Similarly, Hong et al. [24] figure out the social affinity among users as strength of relation is an imperative factor in a social network.

b) *Selection:* The users who have similar evidence have more chances of being connected in a social network like U1 and U3 are similar users based on their rating patterns as depicted in Figure 1. Jeckmans et al. [31] employed trust factor and applied deep learning technique as users trust friends more than unknown persons; the results signify that more reliable recommendations are generated. Similarly, Eirinaki et al. [23] also utilized trust factor to generate recommendations. Recently in 2019, Bok et al. [32] applied collaborative filtering and relationship analysis to suggest events. The proposed method achieves more promising results.

c) *Correlation Influence:* The users are influenced by similar users that are connected on a social network. The similarity can be in the form of likings, disliking, similar tagging, and rating patterns like U1's decision of consuming any service will be more influenced through U3 as compared to any dissimilar user as shown in Figure 1. Huang et al. [33] proposed a modified Bayesian model that incorporates preferences of users in the form of tags and utilized social network relations and results justify that recommendation quality is improved to a greater extent.

d) *Transitivity:* The users are also influenced by the indirect relation that is friend-of-friend like U1 and U6 are indirect friends as U1 is a friend of U5 and U5 is a friend of U6, as shown in Figure 1. Recently in 2019, Yuan et al. [34] proposed a novel graph kernel based link prediction method that uses a social network's structural information and observed that indirect neighbors also influence the strength of social relation.

2.3. Social Recommendation Systems Taxonomy

This sub-section presents the taxonomy of social recommendation systems devised from the existing literature study that describes the proposed approaches, challenges faced with the current techniques and future research directions that serve as areas of improvement in this field. In the past few years, social recommendation systems have gained huge success as it has become an integral part of every social platform. The researchers are consistently working due to its wider range of applicability towards multiple social platforms and provide benefit to online retailers as well as end-users [27-29,31,32]. In this section, the classification scheme of social recommendation approaches is described along with the advancements done in this field. It is broadly classified into three categories as shown in Figure 2 and detailed in subsequent sections below.

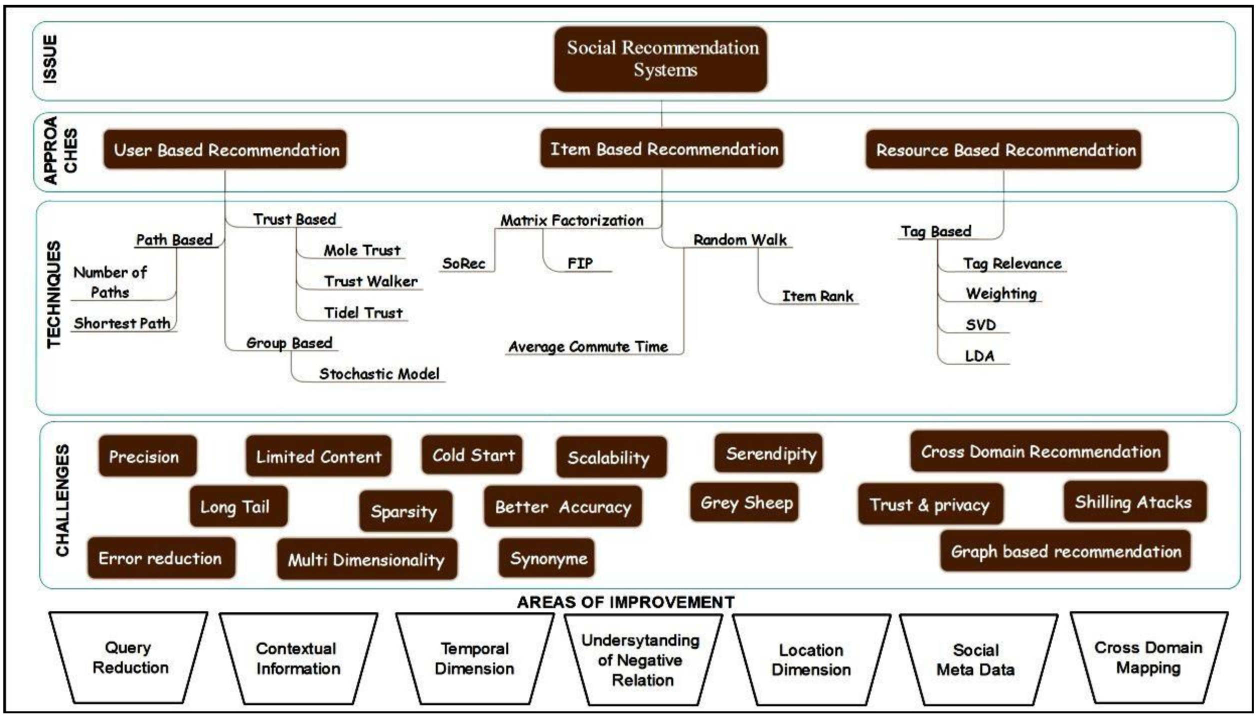

Figure 2. Social recommendation systems taxonomy with related types of approaches, research challenges, annotated with areas for improvement

2.3.1. User-Based Recommendations

These recommendations are user-centric also known as memory-based social recommendations [35] that suggest items to users based on the other similar users available in the social network. One approach to finding similar users is based on the rating patterns using Pearson Correlation coefficient also known as collaborative filtering based social recommendations. Then, these ratings are aggregated to compute the prediction of ratings. The major drawback of this approach is it is slow in prediction of ratings as it stores the entire social network's rating information and has no learning phase [26,36]. The researchers in their work [37] compared collaborative filtering with social filtering; the results signify that social filtering performs better in sparse situations as utilization of social information makes the network dense.

The other factor that is prominently used in the existing study to find similar users is trust factor, as the strength of the relations impacts the accuracy of recommendations [22,23,38]. The various trust metrics [39] have been developed to evaluate that is local trust metric that predicts trust value for every user individually and global trust metric predicts the trustworthiness of a user based on the group as a whole. The researchers developed Tidal Trust [40] that utilizes trust information based on shorter propagation paths. Path among the nodes with high value of trust is more associated with each other. The researchers [41] proposed MoleTrust that overcome the major limitation of TidalTrust [40] by eliminating the cycles created in such networks. Trust is calculated initially with directly connected neighbors and then with users at the next level that is two levels away from the root. In this way, trust with users who lie within the specified maximum depth and rated the target item is calculated. This widens the scope of opinions retrieved from multiple users connected to a network. The researchers proposed TrustWalker [42] and utilized user-oriented information along with trust information that gives more promising results. Recently, Deng et al. [43] proposed a novel matrix factorization method and applied deep learning technique to learn the latent feature vector of users and items. The results signify that utilization of deep learning technique outperforms the baseline methods and in future work can be extended to include time information too.

Further, similar users can be computed using link prediction that utilizes various metrics in the form of neighbor-based metrics. Common neighbors, Jaccard coefficient; path-based metrics can be used to compute the path between nodes. Local path includes Katz, FriendLink, Relation Strength Similarity (RSS); random walk based metrics include hitting time, average commute time, and SimRank [44,45]. Recently in 2019, authors proposed a graph kernel based link prediction method [46] that computes similarity among sub-graphs with different strengths of relation. Then, the similarity is computed among sub graphs. The results signify that it has better performance on both positive and negative links.

2.3.2. Item-Based Recommendations

These recommendations are item-oriented that suggest items to the target user based on the similarity among the items that are computed using item features, descriptors, and latent vector space of items. Most of the models under this category are based on matrix factorization method that utilizes social information and features learned from the item and social information [47,48]. The authors [49] proposed probabilistic matrix factorization based social recommendation systems. SoRec utilizes user-item rating matrix information along with user-user relation matrix to generate recommendations and resolve the sparsity and cold-start problems of traditional recommendation systems. Further, ensemble based method, Social Trust Ensemble and STE [50] uses users and their social network information that have similar ratings for different items. SocialMF [47], a social regularization based method, emphasizes users' interests and is based on the assumption that users connected in a social network have similar interests.

Further, the work is carried out in the direction of integration of other social information like trust value with the latent features vectors of users and items. The authors proposed a modified random walk model that combines trust information and item-based collaborative filtering approach. It not only considers ratings of target item, but also ratings of similar items [42]. The results signify that it outperforms collaborative filtering and pure trust based methods, but ascertained to incorporate contextual information in the future. In 2019, [51] proposed a novel social recommendation model that integrates social interaction, trust values item popularity, ratings and reviews. The results signify that integration of the multiple features leads to better recommendation performance.

2.3.3. Resource-Based Recommendations

These recommendations refer to the computation of similar users and items based on the resources like tags shared on the social networks [52]. The authors define two metrics to evaluate tags-tag relevance: that defines the relation between tag and item to which the tag has been assigned and tag preference: opinion of the user towards a tag [53-55]. In 2010, researchers [56] proposed a content based recommendation model that builds user profiles based on weighted tags but needs to further develop collaborative filtering based recommendation model. Then, in 2014, Huang et al. [53] in their work utilized tag-information to create user profiles. Since the user interests may change over time, so the proposed collaborative filtering based method considers recent tag information to match the user's interests. The results signify that it outperforms the traditional recommendation systems but it can be further extended to incorporate other valuable information like trust factor, follower and following relationships too. In 2019, researchers [57] proposed a collaborative filtering based method that computes similarity among users based on trust values which are calculated based on their tagging behavior but need to be further analyzed for cold-start users.

2.4. Datasets Used in Literature

Data is the most important element of research; availability of datasets publicly would help researchers in the innovation of new ideas and implement them to enhance the performance of existing algorithms too. This sub-section lists the few popular datasets that are available in literature [24,25,35] relevant to social recommendation systems. The few most popular datasets are Epinions: products, Flixster: movies, Ciao: products, Last.fm: music, Flickr: photos, Movie-Tweetings: movies, Douban: items, Bibsonomy: tags, Delicious: tags, Digg: web-pages, Cyworld: digital items, Phoaks: web pages, FilmTrust: multimedia, Lokalisten: restaurants and many more.

3. Research Challenges

Though the social recommendation systems have overcome the drawbacks of traditional recommendation systems like the sparsity problem, similarity is computed with less users which leads to inaccurate recommendations. The other major issue is cold-start issue that happens when a user is new to the system, then preferences of such users are unknown to the system; thus, less reliable recommendations are generated [1,2]. Social recommendation systems are capable of tackling such issues by utilizing their social information along with the user's information connected within their social circles. The social recommendation systems have been well established in the past few years, but there are still some challenges that are confronted due to the complex and dynamic nature of social networks [18,24,26,28,30]. A few of the critical research challenges are discussed in the subsequent sub-sections.

Interpretation of trust*:* Trust in social networks is an important factor as trusted relations in connected network are more reliable. Users trust their suggestions more as compared to casual connections [22,23,38-40,43]. But the trust factor has different interpretations in different contexts. In case of e-commerce platforms, trust factor may relate to reviews submitted for diverse set of products. For Facebook platform, trusted relations can be in the form of similar posts. Due to different interpretations, further analysis can be done on this factor to improve the recommendation performance.

Analysis of huge content: The tremendous engagement of social activities on social platforms generates huge content like reviews, comments, posts, likes, and dislikes which are either structured and unstructured data [22,34]. The researchers have worked on the analysis of such big and unstructured data but it is still an open challenge.

Generating recommendations for group as a whole: It is comparatively difficult to satisfy an individual's preferences in a group [2] as a whole. Ratings submitted earlier for certain items also impact the ratings submitted towards different items later due to variation in individual's interests.

Shilling attacks: Social platforms are more vulnerable to shilling attacks [25,27] as some malicious users with fake profiles inject false ratings and manipulate the actual recommendation rankings for generation of maximum revenue. The researchers have worked on tackling shilling attacks issue but this needs to be analyzed further for better performance.

Difficult to collect feedback: It is tedious to procure a large amount of feedback in comparison to ratings as in social networks feedback is to be collected for a specific role or relative to some context.

Noisy connections: The users connected in a social network have mixed relations with each other; some are trustworthy connections and others are casual connections [30]. Such casual relations become noisy connections that might perform even worse than traditional recommendation systems in case of large network distance.

Varying strength of link: The strength of the relation connecting the nodes in a network varies as it depends on multiple factors [34]. The situation of tie in strength of the relations needs to be inspected further as it makes an association between nodes of asymmetric nature.

In addition to the above research challenges, a few are mentioned [11,19,20,26] in Figure 2. Precision is new algorithms developed to attain better and accurate recommendations; scalability is one of the major issues in social networks as generation of huge content on web increases the network traffic which deteriorates the overall performance of the network on expansion of nodes in a network. Serendipity is to discover that recommendations should be useful; it should not be generated by chance and is difficult to identify grey sheep users as these are inconsistent users who disagree with the other users connected in a network. Thus, it becomes difficult to generate recommendations for such users.

4. Future Research Directions

This section discusses the future extensions that can open up new avenues in the field of social recommendations systems research. The below mentioned areas require more innovative approaches to maximize the performance of social recommendation systems along multiple key dimensions.

Heterogeneity among relations in social networks: In the existing research, the social relations are mainly considered of homogeneous nature. But in fact, associations are of mixed form, as one user might contact other user connected in the same network for suggestions of movies and other users for suggestion of books. This heterogeneity in relations can improve the quality of recommendations [26]. In 2019, researchers proposed a graph neural network (GraphRec) [58] that integrates social interactions and preferences of users in a single user-item graph to address the heterogeneous strength of the relation. But the social and rating information is static and does not include the other contextual information.

Incorporation of temporal information in social networks: The dynamic nature of social networks and varying interests of users with time. At time t1 users love to watch action movies, but after some duration say at time t2, user wish to get suggestions of comedy movies. This demands an efficient temporal social recommendation system. Researchers have started working but it is still not fully developed due to less availability of datasets with temporal dimension and inclusion of time information makes the network structure more complex as user and items evolve with time [59]. Most of the work does not generate recommendations in real time as a part of dataset is taken into consideration. In 2019, researchers proposed a novel dynamic graph-based embedding (DGE) model [60] that models social interactions and behavior patterns and generate recommendations in real time. Though it outperforms the baseline methods, work can be extended to include global information and other deep learning models can be evaluated. Thus, proper identification of matching nodes and determination of strength of relation at varying times are challenging tasks.

Mapping of cross-domains: The increasing interests of users towards multiple social platforms have raised the expectations of users and now a user expects recommendations to be generated in view of varying interests across multiple domains [8,17,18,61]. For instance, if a user likes movies of action genre on Netflix, the user might expect books of action genre from other platforms. But the main challenge is mapping of the data and transferring learning from one domain to other; this area requires further exploration.

Privacy of sensitive data: Nowadays, recommendations have become an integral part of social networks and the tremendous growth of users on multiple social platforms has raised privacy concerns [31]. A user is concerned about his personal and sensitive information that should not be compromised at cost of accuracy; there should be tradeoff between privacy and accuracy. Various techniques have been proposed to address the privacy concern but more approaches to preserve the privacy of users as well as their data are needed.

Extension to distrust relationships: In addition to interests/liking of users towards different products, the interaction or relation among users also affects the performance of social networks recommendations. In the existing literature, more work is carried out on trusted relationships in a network like various trust metrics have been proposed to evaluate the strength of relation [42]. It has been observed that extension to negative relations in form of distrust or dislikes can also enrich the recommendation list. The major challenge is the propagation of distrust information in a network; this requires novel approaches to tackle such negative relations efficiently.

Recommendation in mobile social networks: The location dimension bridges the gap between actual world and social network. With the advancements in technology, users can share their location using GPS feature enabled on mobile phones. Various location-based social networks have been established but it is still in the developing stage due to the availability of less content growth in such networks as now suggestions are not to be fetched only based on users' interests rather in accordance to their proximal locations too [48,62]. This appeals to the interests of users and seed researchers to further work on this aspect of recommendation systems.

Context based trust models: In the existing literature, various pure context-based and trust-based recommendation systems have been well established [13,22]. The trust models have been integrated with content-based and collaborative filtering approaches and achieved promising results. In real scenarios, the degree of trust may vary in different contexts; Thus, incorporation of contextual information along with trust factor would further enhance the performance of social recommendation systems.

The existing social recommendation systems have worked along multiple dimensions as discussed in section 2. But to improve the capabilities of existing social-network based recommendation systems, the research gaps and new trends have been identified to make this area more rich and full-fledged in different aspects. The exploration in the above mentioned research directions would make the foundation stronger, which is the next step in designing a better, unified social recommendation system.

5. Conclusion

In recent years, there has been tremendous growth of social media content in the form of images, text, comments, reviews, tweets, retweets, posts, likes, and dislikes that emerges the need for social recommendation systems. A large number of novel and innovative methods have been proposed in the past few years but it is still an active area of exploration. This paper provides a comprehensive review detailing key concepts, factors affecting the recommendations generated in social networks, classification of social network based recommendations approaches, and a few popular publicly available datasets are listed to properly organize the current work accomplished in the existing literature. In addition to this, research challenges confronted in this domain are outlined to serve as further areas of improvement. Future research extensions are also specified that might serve as a basis for further experimentation in this field. This survey paper would help the researchers, academicians and industry experts to enrich their knowledge base and stimulate new ideas for further advancements in this field.

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