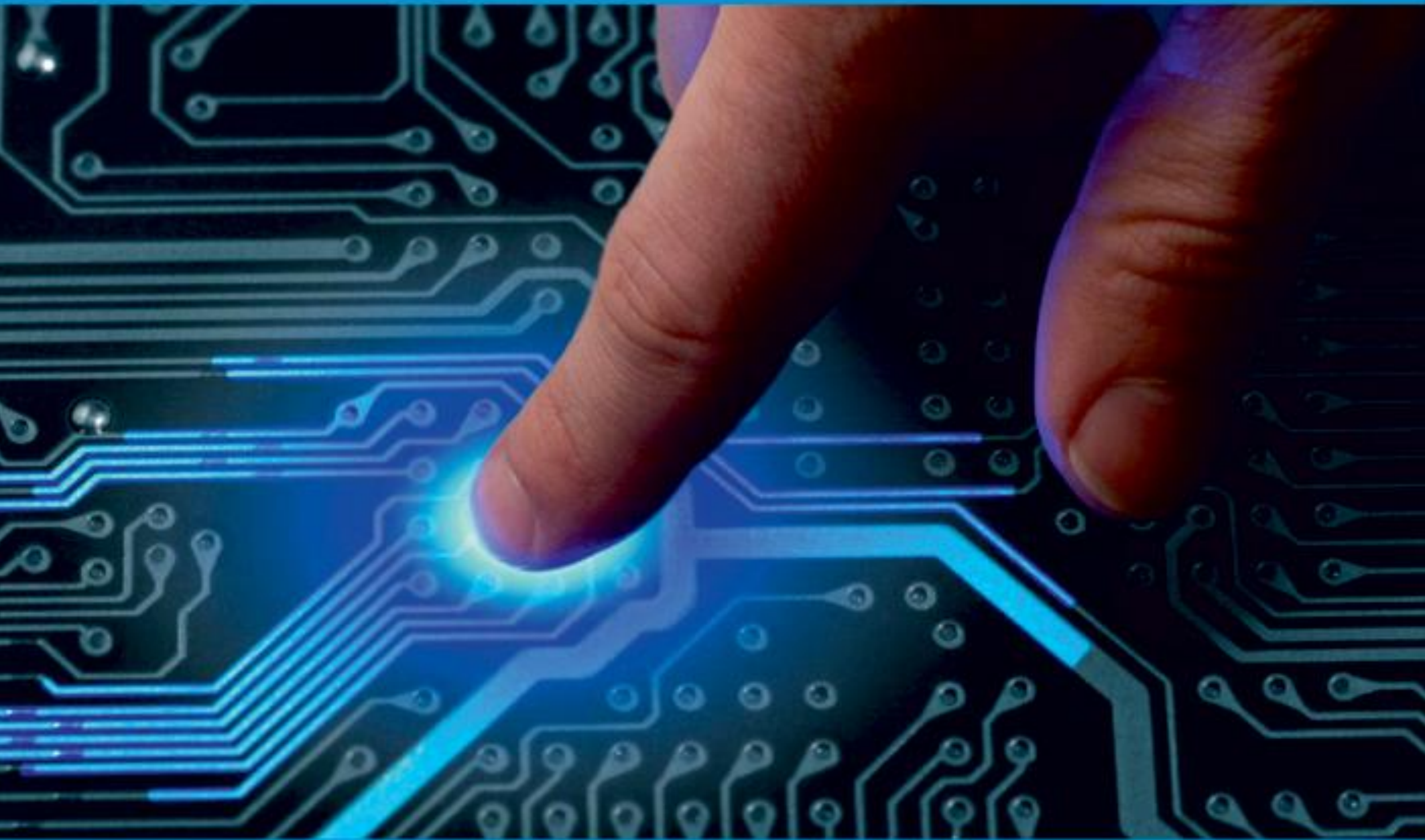
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 5, May 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1205099 |

On Demand Food Delivery with Attention Using LSTM

Mr. A. Akilan, S. Arjun

Assistant Professor, Department of Computer Science and Engineering, MRK Institute of Technology, Kattumannarkoil, Tamil Nadu, India

Department of Computer Science and Engineering, MRK Institute of Technology, Kattumannarkoil, Tamil Nadu, India

ABSTRACT: The research of new restaurant-recommendation systems is very important. Many consumers tend only to order in restaurants they know because they fear disappointment and do not explore other options. Therefore, this recommendation system is vital for consumers and restaurants since it can give an excellent suggestion on where to order next with high accuracy based only on clients' previous orders. The convolution unit is responsible for capturing spatial attributes, while the LSTM part is adopted to learn temporal attributes. Additionally, an attentional model is designed and integrated to enhance the prediction performance by addressing the spatial variation in demand. The proposed approach is compared to several baseline models using a historical ODFD dataset from Shenzhen, China. Results indicate that the proposed model obtains the highest prediction accuracy by capturing both spatial and temporal correlations with attention information focusing on different parts of the input series. The recommendations will satisfy the clients, and restaurants can increase their sales. The future scope of this research can involve the implementation of this methodology in other areas. For example, recommendations for online sales or bookstores. Likewise, the system could be evaluated in a larger-scale real-world study to further validate its effectiveness in practice.

KEYWORDS: food delivery; recommendation system; nearest neighbors; number of orders

I. INTRODUCTION

Information retrieval is that the process of selectively disseminating relevant information stored among a spread of data objects. A useful method of storing these objects adopts the notion of clustering, where similar objects are placed into homogeneous groups with the expectation that objects within an equivalent group are similar and certain to be relevant to an equivalent queries. In this project, we propose a replacement approach for an intelligent retrieval framework with feedbacks and reviews given by the purchasers on each food delivery applications and analyze the gathered information about reviews and ratings from the food delivery applications and therefore the rank the applications with the assistance of the gathered information on feedback and reviews by using various ranking algorithms. Also there are various applications on the web which compare differing types of knowledge during a particular domain for eg. Trivago which compares various hotels and provides best deal then after clicking on the "view deal" button, similarly in our system we compare two apps which are swiggy and zomato. On the idea of reviews and ratings which can show top three restaurants on the idea of user reviews, swiggy ratings and zomato ratings.

The prediction of ODFD demand belongs to the family of spatial–temporal predictions. Previous studies are mainly based on statistical models and machine learning, including the time series ARIMA approach, regressions, Bayesian network (BN) models, and so on. Although these approaches have alleviated the prediction difficulties, most of them do not consider spatial–temporal correlations in the demand. With traditional model structures and estimation algorithms, it can be difficult to incorporate such spatial information into predictions. In recent years, deep-learning-based approaches have been widely used for demand predictions, including bike usage prediction, ride-hailing demand–supply prediction, and so on. Specifically, convolutional neural networks are capable of capturing spatial–temporal correlations in transportation prediction problems. Recurrent neural networks and their extensions such as long short-term memory are well fit for processing time series data streams.

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1205099 |

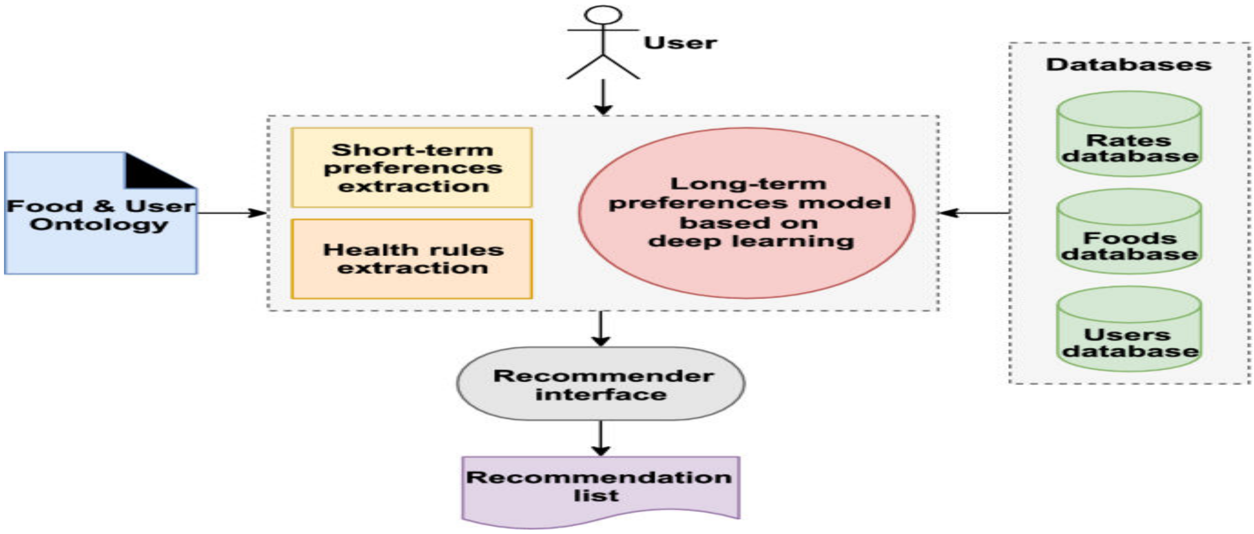


Fig 1: FoodRecNet

To tackle these challenges, this paper proposes an attention-based convolutional long short-term memory (At-ConvLSTM) method to perform short-term forecasting of ODFD demand at the city scale. The main contributions are three-fold. First, the spatial–temporal correlations between different regions for sent demand and received demand are captured by a combination of convolutional units and LSTM layers. Specifically, convolutional neural network (CNN) layers are utilized to enhance the extraction of spatial features, while LSTM layers are adopted to capture the short- and long-term sequential pattern information. Second, an attention model is designed and incorporated to further improve prediction accuracy. Specifically, it addresses spatial variation in demand by assigning weights to demand in different regions for each forecast step. Third, the proposed At-ConvLSTM is illustrated using a historical ODFD dataset from Shenzhen, China. Results show that it outperforms several baseline approaches, and discussions are also provided

II. LITERATURE SURVEY

Yayuan Tang, Hao Wang, Kehua Guo, Yizhe Xiao, And Tao Chi, “Relevant Feedback Based Accurate and Intelligent Retrieval on Capturing User Intention for Personalized Websites”, April 2018. With the rapid climb of networking, cyber–physical–social systems (CPSSs) provide vast amounts of data. aimed toward the large and sophisticated data provided by networking, obtaining valuable information to satisfy precise search needs when capturing user intention has become a serious challenge, especially in personalized websites we use real-time location and relevant feedback technology to style and implement an efficient, configurable, and intelligent retrieval framework for personalized websites in CPSSs. to enhance the retrieval results, we propose a technique of implicit relevant feedback supported click-through data analysis, which may obtain the connection between the user query conditions and retrieval results Pratiksha Ashiwal, “Web Information Retrieval Using Python and Beautiful Soup”, June 2016.

There are number of approaches by which the live data are often obtained for research and development. One among these approaches is getting data from OpenData Portals. The open data portals provide authentic data sets for research and development in multiple domains. the info sets can be downloaded from these portals in multiple formats including XML, CSV, JSON and lots of others. Many times data isn't easily accessible although it does exist. the maximum amount as we wish everything was available in CSV or the format of our choice – most data is published in several forms on the online. I. K. C. U. Perera “Aspect Based Opinion Mining on Restaurant Reviews,” 2017. Every day, people within the world share their experience and thoughts regarding various products and services on the World Wide Web.

These are called opinions which are valuable in the decision-making process. Therefore, the World Wide Web has become a huge repository containing different quite of opinions and thoughts of the people. However, to urge benefits from these accumulated opinions, the contents should be extracted in to features such as “food”, “services”, “environment” within the restaurant domain and analyzed properly since those opinions are written in complex sentences and in the row text format. Data mining extracts the hidden knowledge from the unstructured texts exists in sort of patterns and relationships. These extracted and analyzed opinions are useful for customers as well as sellers

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1205099 |

since they will get a concession evaluating others' opinions associated with the merchandise or services intended to get. Hence people cannot read billions of opinions manually and it's difficult to extract the important ideas from them. Data Mining techniques provide promising solutions to resolve the aforementioned issues.

Several studies focus on investigating the spatial–temporal patterns of ODFD usage found in their research on food accessibility and built environment, the utilization of ODFD is primarily observed in densely populated urban regions, particularly in city centers and sub-centers. Moreover, a greater number of ODFD orders are observed in areas where walking for food access is less convenient but cycling for food access is more convenient. Later on, found that food delivery demand could also change the built environment in the long term. mapped the distribution of takeaway food demand across China based on the analysis of more than 35 million takeaway food orders. Their results also indicate that ODFD demand is higher in densely populated or economically developed cities, and that demand varies greatly and regularly across different time intervals. used an enhanced two-step floating catchment area (E2SFCA) approach to quantify the accessibility of ODFD in a city. The results imply that ODFD demand is more concentrated in the core area of the city, and the farther away from the city center, the less service ODFD can provide. These studies indicate that the ODFD usage is not randomly distributed across the city; instead, it exhibits latent spatial–temporal patterns.

III. PROPOSED SYSTEM

Various algorithms are used to implement this project. Researchers have made great effort to improve the efficiency of information retrieval. The most common approach is based on keywords. Substantial current research work only considers single keywords without fully expressing the intentions of users. In expanded research, others use related multi-keywords queries, which make the query results more consistent with the user's requirements.

It is used to identify the aspect related opinions. Opinion mining may be a data mining technique. It uses Natural Language processing. This is finished restaurants and there are various reviews which is written by customer. It is hardly possible to read all the reviews so that is why to offer the thought a few particular restaurant opinion mining may be a solution.

Subjective and Objective-Subjective sentences are classified into binary scale and multivariate scale. Binary scale classifies opinion as either positive or negative whereas multivariate scale classifies opinion as a like rating scale which may be 3 point, 5 point. It is used helps to extract the emotions involved within the opinion. Basic emotions are classified into six categories (i.e. Anger, Fear, Sadness, Enjoyment, Disgust and Surprise).

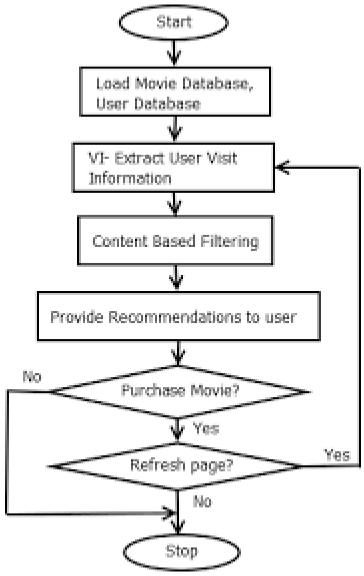


Fig 2: Work Flow

Unlike traditional urban logistics based on known demand, a customer's request may arrive at any time and any place, while the status and location of riders also changes with time. In some cases, no delivery person may be available in the

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1205099 |

vicinity of a request, creating high waiting times and, consequently, order cancellations. Minimizing delays and improving use satisfaction for ODFD service requires effective assignments between orders and riders. Moreover, the amount of time elapsed between the order being picked up and the receipt of the food could vary due to numerous random elements. Therefore, even if the send-out demand is known, the platform does not know exactly when the order could be delivered.

In this study, we predict the send-out demand and the received demand separately, which is helpful for ODFD platforms to respond to immediate requests from customers and hedge the uncertainty in demand prediction. For instance, with future send-out demand, it is possible for the platform to bundle multiple orders to a single rider nearby or guide idle riders waiting near locations where new requests are more likely to occur. Meanwhile, with predicted received demand, the platform could make better assignment decisions based on the status of orders and riders. New emerging requests can be assigned to those riders that could finish delivery within a short time.

IV. EXPERIMENTS AND RESULTS

Since our metric for calculating the recommendations' performance removes one of the preferred restaurants for each client, it is important to know the number of preferred restaurants is modified when varying the parameter of *pmin*. It can be observed that by using 5% as the minimum percentage for considering a restaurant as one of the favorites, we have around five restaurants among the client's preferences. As expected, if the value of *pmin* increases, the number of preferred restaurants decreases. If we consider a minimum percentage of 10% (as recommended), we have around 2.6 preferred restaurants. Based on the dataset used for this research, we do not recommend a value of *pmin* greater than 0.1 because the number of preferred restaurants is very small (≦≦2). In addition, values smaller than 0.1 indicate that we need less than 10% of our orders to consider a restaurant to be one of our favorites.

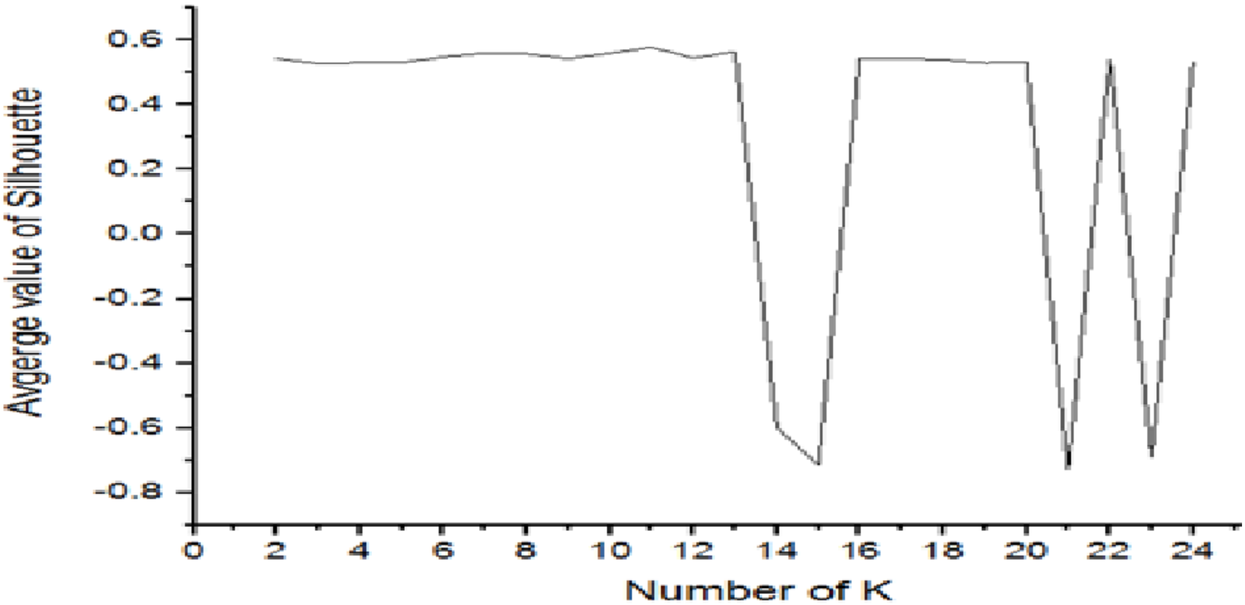


Fig. 3 The relation between computed-K and clustering results (k=11)

Fig 3: Food Result analysis

The dataset encompasses 21-day spatial-temporal data on ODFD orders on the Ele.me platform in Shenzhen, China, as shown in. In total, it contains 1,048,576 delivery records. Each record contains the starting/ending time and location, as well as the number of orders that the couriers served simultaneously. Orders with coordinates outside of city edges, too short delivery time (e.g., <1 min), unreasonable delivery speed, and identical senders' and receivers' coordinates are removed as outliers. After data filtering, 879,947 records were kept for subsequent analysis. The filtered dataset still has an average of about 40,000 data records per day, which is sufficient to support the subsequent research.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1205099 |

V. CONCLUSIONS

This document proposed a recommendation system for a delivery food application based on orders. Our system uses the sales transactions automatically stored by the application, and no questionnaires or ratings are needed from customers. The methodology used for the recommendation is a nearest-neighbor technique that is based on the percentage of orders. The recommendations are based on the preferred restaurants. We defined a preferred restaurant as one with at least 10% of the clients' orders. In our experiments, we used actual data from a local delivery food application with 187 restaurants and 100 customers in Aguascalientes, Mexico. Clients have, on average, only 2.6 preferred restaurants, and 24% of the time, our system can identify one of those preferred restaurants from a list of 7.7 recommended ones (from 187 available). These numbers confirmed to us that our system has a satisfactory performance.

Previous proposals from the literature used ratings and reviews as training data. However, only some clients proportionate that information after their purchases. This makes the implementation of recommendation systems in real delivery food applications difficult. This research's main contribution is using the number of orders as input for the recommendation system. These data are always stored and available in the delivery food applications. Therefore, our methodology enables the implementation of a restaurant-recommendation system in real-life scenarios.

REFERENCES

1. Poniszewska-Maranda, A.; Matusiak, R.; Kryvinska, N.; Yasar, A.U.H. A real-time service system in the cloud. *J. Ambient Intell. Humaniz. Comput.* **2020**, *11*, 961–977. [**Google Scholar**] [**CrossRef**]
2. Poniszewska-Maranda, A.; Kaczmarek, D.; Kryvinska, N.; Xhafa, F. Studying usability of AI in the IoT systems/paradigm through embedding NN techniques into mobile smart service system. *Computing* **2019**, *101*, 1661–1685. [**Google Scholar**] [**CrossRef**]
3. Tegene, A.; Liu, Q.; Gan, Y.; Dai, T.; Leka, H.; Ayenew, M. Deep Learning and Embedding Based Latent Factor Model for Collaborative Recommender Systems. *Appl. Sci.* **2023**, *13*, 726. [**Google Scholar**] [**CrossRef**]
4. Palomares, I.; Porcel, C.; Pizzato, L.; Guy, I.; Herrera-Viedma, E. Reciprocal Recommender Systems: Analysis of state-of-art literature, challenges and opportunities towards social recommendation. *Inf. Fusion* **2021**, *69*, 103–127. [**Google Scholar**] [**CrossRef**]
5. Ali, S.M.; Nayak, G.K.; Lenka, R.K.; Barik, R.K. Movie recommendation system using genome tags and content-based filtering. In *Advances in Data and Information Sciences*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 85–94. [**Google Scholar**]
6. Wang, S.; Gong, M.; Wu, Y.; Zhang, M. Multi-objective optimization for location-based and preferences-aware recommendation. *Inf. Sci.* **2020**, *513*, 614–626. [**Google Scholar**] [**CrossRef**]
7. Wang, F.; Hu, L.; Sun, R.; Hu, J.; Zhao, K. SRMCS: A semantic-aware recommendation framework for mobile crowd sensing. *Inf. Sci.* **2018**, *433*, 333–345. [**Google Scholar**] [**CrossRef**]
8. Fedushko, S.; Ustyianovych, T.; Syerov, Y. Intelligent academic specialties selection in higher education for Ukrainian entrants: A recommendation system. *J. Intell.* **2022**, *10*, 32. [**Google Scholar**] [**CrossRef**]
9. Lee, S.K.; Cho, Y.H.; Kim, S.H. Collaborative filtering with ordinal scale-based implicit ratings for mobile music recommendations. *Inf. Sci.* **2010**, *180*, 2142–2155. [**Google Scholar**] [**CrossRef**]
10. Iwendi, C.; Khan, S.; Anajemba, J.H.; Bashir, A.K.; Noor, F. Realizing an efficient IoMT-assisted patient diet recommendation system through machine learning model. *IEEE Access* **2020**, *8*, 28462–28474. [**Google Scholar**] [**CrossRef**]
11. Addagarla, S.K.; Amalanathan, A. Probabilistic Unsupervised Machine Learning Approach for a Similar Image Recommender System for E-Commerce. *Symmetry* **2020**, *12*, 1783. [**Google Scholar**] [**CrossRef**]
12. Zhang, X.; Liu, H.; Chen, X.; Zhong, J.; Wang, D. A novel hybrid deep recommendation system to differentiate user's preference and item's attractiveness. *Inf. Sci.* **2020**, *519*, 306–316. [**Google Scholar**] [**CrossRef**]
13. Luo, Y.; Xu, X. Comparative study of deep learning models for analyzing online restaurant reviews in the era of the COVID-19 pandemic. *Int. J. Hosp. Manag.* **2021**, *94*, 102849. [**Google Scholar**] [**CrossRef**] [**PubMed**]
14. Zhang, C.; Zhang, H.; Wang, J. Personalized restaurant recommendation method combining group correlations and customer preferences. *Inf. Sci.* **2018**, *454*, 128–143. [**Google Scholar**] [**CrossRef**]
15. Wang, L.; Yi, B. Research on O2O take-away restaurant recommendation system: Taking ele. me APP as an example. *Clust. Comput.* **2019**, *22*, 6069–6077. [**Google Scholar**] [**CrossRef**]
16. Marques, G.; Respício, A.; Afonso, A.P. A mobile recommendation system supporting group collaborative decision making. *Procedia Comput. Sci.* **2016**, *96*, 560–567. [**Google Scholar**] [**CrossRef**]
17. Gartrell, M.; Alanezi, K.; Tian, L.; Han, R.; Lv, Q.; Mishra, S. SocialDining: Design and analysis of a group recommendation application in a mobile context. *Comput. Sci. Tech. Rep.* **2014**, *10*, 1034. [**Google Scholar**]