IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Eatery Spot Recommendation System using Location Based Social Networks

1Harshit Singh, 2Akshay Mathur, 3Ayush Raj Gupta, 4Mohammed Tamir, 5Ms. Ankita Gupta
1Bachelor’s Student, 2Bachelor’s Student, 3Bachelor&039,s Student , 4Bachelor&039,s Student ,
5Assistant Professor IT
1Babu Banarasi Das Northern Indian Institute Of Technology, Lucknow ,
2Babu Banarasi Das Northern Indian Institute Of Technology, Lucknow ,
3Babu Banarasi Das Northern Indian Institute Of Technology, Lucknow ,
4Babu Banarasi Das Northern Indian Institute Of Technology, Lucknow ,
5Babu Banarasi Das Northern Indian Institute Of Technology, Lucknow

Abstract: With the increasing popularity of location-based social networks (LBSNs) and theabundance of food-related content shared by users, there is a growing interest in developing eatery spot recommendation systems that leverage LBSN data. This research paper proposesa system (ESRS) that utilizes LBSN data to recommend personalized dining options to users based on their location, preferences, and. The ESRS employs a hybrid recommendation approach, combining collaborative filtering techniques with geographical proximity analysis and user feedback to enhance the dining experience of users. The ESRS not only enhances the dining experience for users but also benefits local businesses by increasing foot traffic and customer engagement. The user feedback mechanisms are integrated to gather real-timeinputs and improve the recommendation accuracy over time. The system aims to address thechallenges of information overload and decision fatigue faced by users when choosing dining venues, ultimately enhancing user satisfaction and engagement in the dining experience.

Keywords:- Recommender System, Collaborative filtering, User feedback, Location based social network

I. INTRODUCTION:

The Eatery Spot Recommendation System (ESRS) in Location-Based Social Networks (LBSNs) represents an innovative approach to enhancing dining experiences by leveraging thepower of social networks and geospatial data. In an era where digital connectivity and mobile technology dominate our daily lives, the ESRS emerges as a solution to address the growing demand for personalized and contextually relevant restaurant recommendations. In recent years, the proliferation of LBSNs has transformed the way people discover and share information about restaurants and food establishments. Platforms such as Yelp, Foursquare, and Zomato have become indispensable tools for consumers seeking dining recommendationsand reviews [4]. However, traditional recommendation systems often fail to capture thenuanced preferences and social dynamics that influence dining choices [1]. The ESRS addresses this limitation by integrating social networking features into the recommendation process, allowing users to leverage the wisdom of their social circles and discover restaurants based ontrusted recommendations from friends and peers [2]. The significance of the ESRS lies in its ability to bridge the gap between online social interactions and offline dining experiences [5]. By leveraging geospatial data and social network analysis techniques, the ESRS enhances the relevance and accuracy of restaurant recommendations, leading to greater user satisfaction and engagement [3]. Moreover, the ESRS has the potential to drive foot traffic to local eateries, support small businesses, and foster community engagement within LBSNs [7].

II. LITERATURE REVIEW:

Various methods are present for the development of restaurant recommendation system. Manyof the existing systems and functioning are as follows.

In this recommender system, they developed recommendations based on preferences of user [1]. It was motivated by the observation that a user's preference against an item is affected by different aspects discussed in reviews [1]. They first explored the topic modelling to discover the hidden aspects from review text [1].

Finally, they utilized regression models to detect the user-restaurant relationship [1].They described the restaurant recommendation system as a very popular service whose accuracy andsophistication keeps increasing every day [2]. They presented a personalized location-based restaurant recommendation system integrated in mobile technology [2]. It ubiquitously studiedthe user's behavioural pattern of recommendation systems and proposed methods to rectify it [2].

In this research, they described the restaurant recommendation system with machine learning algorithms [3]. In order to find a good machine-learning model, they have tried several collaborating filtering methods to predict ratings between restaurants and users [3]. Themethods they have implemented are Slope One, k-Nearest Neighbours algorithm, and multiclass SVM classification [3]. Their evaluation shows that the multiclass SVM classification method outperforms the other methods [3].

For rating prediction, they compare user-based and item-based collaborative filtering algorithms [4]. Finally, architecture is given to support the building of a real-time recommendation service [4].

In this proposed system, they had used SVM to predict the restaurant based on the user location[5]. By developing a recommendation system which could help a user to decide whichrestaurant one should visit, the person can save a lot of his time, efforts, and money and thus have a great experience and satisfaction [5].

There are various factors based on which a user decides of visiting a restaurant like the type ofcuisine of the restaurant, the location of the restaurant, the ambiance, price range, popularity, ratings, etc. Such information is collected and made available on sites such as Yelp and Zomato[2][6].

Using well-rounded, open-source dataset provided by Yelp which provides data not only of therestaurant reviews, but also user-level information on their preferred restaurants the aim is to build an efficient recommendation system for the Yelp users in the form of a softwareapplication and thus help them predict whether they will like visiting a restaurant or not by applying machine learning techniques and algorithms [7].

In addition to the described methods, recent advancements in restaurant recommendation systems have focused on leveraging Location-Based Social Networks (LBSN) data to enhanceuser preferences and recommendations [8]. These systems take into account not only the user's

explicit preferences but also implicit signals derived from their interactions and behaviours within LBSN platforms [8]. For instance, geolocation data can be used to recommend restaurants based on proximity, offering users personalized and contextually relevant suggestions [8].

Furthermore, integrating sentiment analysis and opinion mining techniques intorecommendation systems allows for a deeper understanding of user preferences [9]. Byanalyzing reviews and feedback from LBSN platforms, these systems can extract valuable insights regarding the quality of food, service, ambiance, and overall user experiences [9]. Thisnuanced understanding enables more accurate and tailored recommendations that align with user expectations and preferences [9].

Additionally, the emergence of mobile technology has revolutionized restaurant recommendation systems, allowing for seamless integration with user devices and real-time updates [10]. Mobile applications equipped with location-aware features can provide on-the-gorecommendations based on the user's current location, preferences, and contextual information,enhancing the overall user experience and convenience [11].

III. METHODOLOGIES:

WORK FLOW:

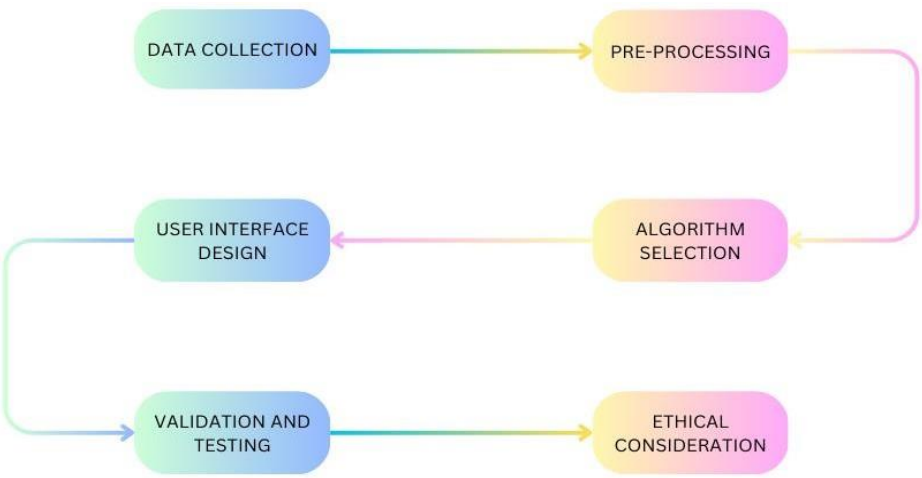

Fig. 1 Workflow Diagram

Data Collection: In this stage the dataset is collected that will be used as research training data. The dataset used is a dataset obtained from one of the dataset provider websites kaggle.com. The parameters of datasets used in this study, are Name, Street Address, Location,Type, Reviews, Number of Reviews, Comments, Contact Number, state, city, latitude, longitude

Pre-processing: At this stage, the author will filter the content contained in each dataset. Thisis done because not all of the content on the dataset will be used during the recommendation making process and lighten when the process takes place. The following is a brief overview ofthe dataset content used in table form:

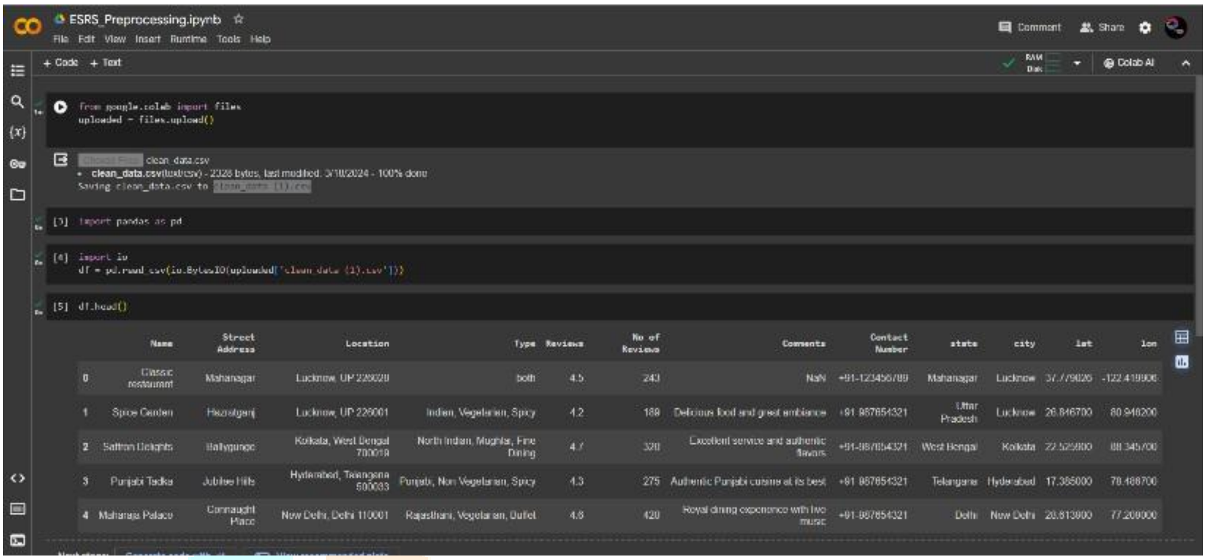

Fig. 2 Sample Data

Fig. 3 Exploratory Data Analysis (EDA) Plots

Fig. 4 Dataframe Shape and Data Types

Algorithm Selection: The selection of algorithms is crucial to ensure accurate, personalized,and context-aware recommendations for users seeking dining experiences.

- **Collaborative Filtering:** In contrast to content-based filtering, this system operates independently of data descriptions, making recommendations without prior knowledge of the products. Collaborative filtering, a type of recommendation algorithm, relies on the ratings or behaviours of other users within the system to generate predictions and suggestions. Its core concept revolves around identifying and leveraging the opinions of fellow users within the community.
- **Content-Based Filtering:** Content-based filtering encompasses techniques that suggest recommendations by evaluating the content attributes of an item against those of user preferences. This approach revolves around matching item descriptors with user profiles, thereby offering suggestions that align with the user's interests through a comparison of content representations.
- **Matrix factorization:** It is a class of collaborative filtering algorithms used in recommender systems. Matrix factorization algorithms work by decomposing the user-item interaction matrix into the product of two lower dimensionality rectangular matrices.

A Recommendation System is an information filtering system that seeks to predict therating a user would give for the item (in this case a restaurant). We can break down the large matrix of ratings from users and items into two smaller matrixes of user featureand item-feature.

We have two matrixes (user-features, business-features) that we can multiply topredict the ratings that a user gives to a restaurant. Later, we need to update thevalues in the features of our two matrixes according to the Error.

To optimize the predictions, we need to calculate the error using the function below.

$$\min_{P,Q} \sum_{(i,x)\in R} (r_{xi} - q_i \cdot p^T)^2 \; x$$

Given P is the users-features matrix and Q is the business-features matrix. If we subtract the real ratings (r) with the predicted ratings (P.Q) and we square it, we getthe LSE(Least Square Error).

To avoid overfitting we have to add regularization to our LSE formula and it willbecome the formula written below.

$$\min_{P,Q} \sum (r_{xi} - q_i \cdot p^T)^2 + \boldsymbol{\lambda} \left[\sum \| \boldsymbol{p_x} \|^2 + \sum \| \boldsymbol{q_i} \|^2 \right]$$

raining x x i

We apply the equation to minimize the error using Gradient Decent to update thevalues of each feature in matrix P and matrix Q.

IV. RESULT

User Interface Design: The user interface (UI) of the ESRS plays a crucial role in providing an intuitive and engaging platform for users to discover, explore, and interact with recommended eateries based on their preferences and location. The design of the UI encompasses several key elements to ensure usability, and functionality.

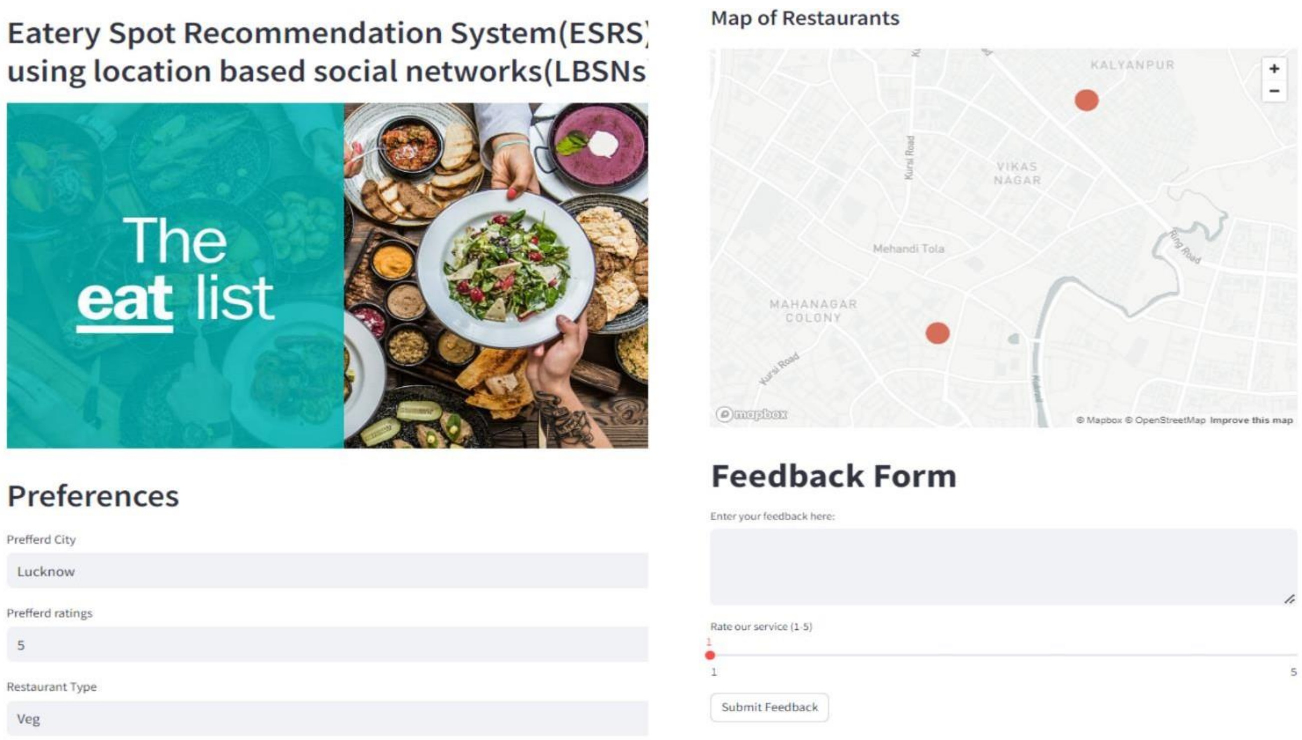

Fig. 5 User Interface

Validation and Testing: The ESRS underwent extensive validation and testing to ensure its robustness, reliability, and effectiveness in delivering accurate and personalized eatery recommendations. The validation process included:

- Data Validation: Ensuring the integrity and quality of the input data.
- Model Validation: Verifying the performance and accuracy of the recommendation algorithms.
- User Testing: Collecting feedback from real users to identify and fix usability issues.
- Beta Testing: Conducting a beta phase to gather insights and make improvements basedon user interaction.
- A/B Testing: Comparing different versions of the system to optimize features and user engagement.
- Performance Evaluation: Assessing the system's overall performance, includingresponse time and recommendation accuracy.

Ethical Considerations: The ESRS adheres to stringent ethical standards, focusing on privacy,security, and fairness

- Privacy and Security Assessment: The system is evaluated for compliance with data privacy regulations such as GDPR. Measures are in place to protect user data, anonymizesensitive information, and ensure secure authentication mechanisms.
- Bias and Fairness Analysis: The system includes analysis to identify and mitigate biasesin recommendation algorithms, such as gender or cultural bias. Efforts are made to implement measures that ensure fair and equitable recommendations for all users, regardless of demographic factors.

V. CONCLUSION:

This highlights the importance of location-based recommendation systems, the integration of LBSNs, and the relevance of dining experiences in the context of ESRS. Building upon existingresearch, this study aims to contribute to the advancement of ESRSs by addressing key challenges and leveraging emerging technologies to deliver personalized and engaging dining recommendations. This literature review section provides a comprehensive overview of relevant literature, establishes the context for the research paper, and identifies gaps or areas for further investigation in the field of Eatery Spot Recommendation Systems using Location-Based Social Networks.

VI. REFERENCE :

[1] Yifan gao, Wenzhe Yu, Pingfu Chao, Rong Zhang, "A Restuarant Recommendation System by Analyzing Ratings and Aspects in Reviews", 20th International Conference, DASFAA 2015, Hanoi, vietnam, 2015.

2] Anant Gupta, Kuldeep Singh, "Location Based Personalized Restaurant Recommendation System for Mobile Environments", International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2013.

[3] Rui Jiang, "A Customized Real Time Restaurant Recommendation System", A Thesis in Computer Science and Engineering "10(2) special 2015.

[4] Anusha Jayasimhan,parikshith Rai, Yash Parekh, Ojas Patwardhan, "Restaurant Recommendation System" International Journal of Computer Applications, Vol.-6, 2017.

[5] Mohammad Salehan, Sonya Zhang, Navid Aghakhani, "A recommender system for restaurant reviews based on consumer segment", AMCIS International Journal of Computerscience, April 2017.

[6] Shuai Zhang, Lina Yao, Aixin Sun, Yong Ge, "Collaborative Filtering with Social Regularization for Restaurant Recommendation," ACM Transactions on Intelligent Systems and Technology (TIST), Volume 6, Issue 2, Article No. 29, 2015.

[7] Liu, Bin, and Huan Liu. "Exploring social context for topic detection and recommendation." Proceedings of the 7th ACM International Conference on Web Search and Data Mining. 2014.

[8] Liu, Yitong, and Geetika Tewari. "Location-based recommendation systems: a research perspective." Proceedings of the 10th International Conference on Pervasive Services. 2014.

[9] Zhang, Shuai, Lina Yao, Aixin Sun, and Yi Tay. "Deep learning based recommender system: A survey and new perspectives." ACM Computing Surveys (CSUR) 52, no. 1 (2019):1-38.

[10] Ricci, Francesco, Lior Rokach, and Bracha Shapira, eds. "Recommender systems handbook." Springer, 2015.

[11] Campos, Pedro G., Álvaro M. Pereira, Iván Cantador, and Ignacio Fernández-Tobías. "Context-aware restaurant recommendation: What, where, and for whom." In Proceedings of the 2014 Conference on User Modeling Adaptation and Personalization, pp. 87-93. 2014.