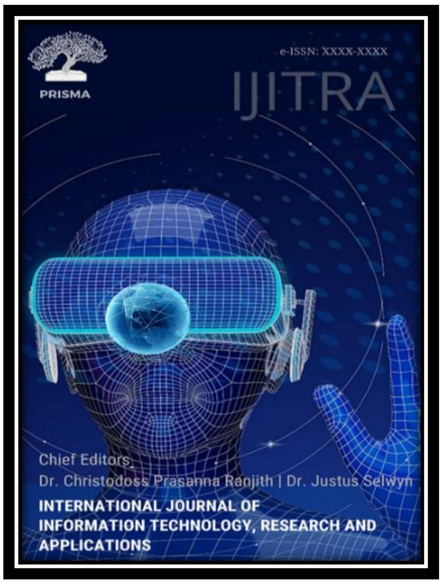

International Journal of Information Technology, Research and Applications (IJITRA)

Ms Sarwath Unnisa, Akshaya N S, (2024). Personalized Mood-Centric Book Recommendation Integrating Machine Learning with Content Based Filtering, 3(3), 15-22.

ISSN: 2583 5343

DOI: 10.59461/ijitra.v3i3.100

The online version of this article can be found at:
https://www.ijitra.com/index.php/ijitra/issue/archive

Published by:
PRISMA Publications

International Journal of Information Technology, Research and Applications (IJITRA) is a journal that publishes articles which contribute new theoretical results in all the areas of Computer Science, Communication Network and Information Technology. Research paper and articles on Big Data, Machine Learning, IOT, Blockchain, Network Security, Optical Integrated Circuits, and Artificial Intelligence are in prime position.

PRISMA
PUBLICATIONS

https://www.prismapublications.com/

Personalized Mood-Centric Book Recommendation Integrating Machine Learning with Content Based Filtering

Ms Sarwath Unnisa[1], Akshaya N S[2]

[1,2]Dept. of Computer Science, Mount Carmel College Autonomous, Bangalore, Karnataka, India

Article Info

Article history:

Received April 01, 2024
Revised August 22, 2024
Accepted September 02, 2024

Keywords:

Mood Assessment
Emotion Detection
Content Based Filtering
Recommendation

ABSTRACT

This paper introduces a novel personalized book recommendation system aimed at enhancing subjective well-being (SWB). Despite the vast array of books available on the internet, people often struggle to find literature that aligns with their current emotional state. The system dynamically detects users' emotional states and recommends books tailored to their mood. It utilizes a content-based filtering algorithm to suggest top-rated books in real-time based on the user's current emotional state. For users with low mood, uplifting and inspirational books are recommended, while a mix of happy and sad books is suggested for happy users to acknowledge the nuanced interplay of emotions. Neutral-themed books are proposed to users with a neutral mood for balance. The system employs an emotion classification algorithm for accurate mood detection, analyzing book summaries to extract emotional tones. Users' emotional states are evaluated using a Likert scale, adjusting recommendations accordingly. The methodology involves data collection, preprocessing, emotion classification, and mood meter operation. Results demonstrate the system's effectiveness in providing tailored book recommendations, enriching users' reading experiences.

Corresponding Author:

Akshaya N S
Dept. of Computer Science,
Mount Carmel College Autonomous,
Bangalore, Karnataka, India
Email: aksha7746@gmail.com

1. INTRODUCTION

In this digital age, where a plethora of information is easily available, the difficulty is not just finding recommendations, but also finding ones that align with our emotional and mental states at the moment. Conventional methods for recommending books frequently depend on elements like author, genre, or user preferences, but they could miss the vital component of mood. Mood-based book recommendation systems provide readers with a customized strategy that takes into account their emotional requirements and preferences, improving their reading experience in general.[1]

Emotion is an element of the contextual factors that many studies on recommendation systems use. This sets off the recommendation process's emotional intelligence. In this paper we propose a recommendation system in this study that leverages the user's current emotion during the suggestion process.[2] Most human emotions can be grouped into fear, scorn, fury, surprise, sadness, happiness, and neutrality. Moreover, there exist numerous other emotions that fit into these categories, like cheerfulness, that embodies happiness, and disdain, that represents disgust. These emotions are highly intricate.[3]

The majority of recommendation systems in use today rely on user ratings. These systems only let you have a static user experience because they provide suggestions based solely on past ratings, disregarding other factors like user behaviour, reaction, feeling, or emotion that could affect the prediction. However, incorporating emotional and behavioural characteristics into machine learning models could unlock a more dynamic, personalized, and customized experience for users. This integration provides the possibility of significant improvement in user satisfaction and engagement.[3], [4]

This paper seeks to build a personalized mood-centric book recommendation system. It will analyse the user's current mood and suggest books based on the predominant mood identified.

2. LITERATURE REVIEW

This comprehensive examination of similar existing research provides context, theoretical frameworks, and insights that guide the formulation of research questions and procedures, and it is the cornerstone around which this research is constructed.

Lately, some academics have made advancements in mood-based recommendation systems. Idrissi proposed a novel method called the "Mood-Genre Fusion Framework" that combines the expressive undertones of moods with the structural characteristics of genres. And performed analysis of extensive user interactions and the application of modern data analytics techniques using book database, web platform feedback and storygraph. Books and metadata were vectorized using TF-IDF (Term Frequency-Inverse Document Frequency) weighting. Next, the closest matches to a user's reading history and declared preferences were found using cosine similarity. [5] One drawback of this system is its inability to capture real-time data, thus potentially failing to accurately reflect the current mood or sentiments of the user.

Borgaonkar et al., proposed a system called Personalized Video Recommendation (PVR) to help users find entertainment. Employing the Local Binary Patterns Histogram (LBPH) and Haar cascade algorithms for emotion, feature extraction, and face identification. The built model will recommend videos based on the emotion it detects. [6] Another drawback is that some individuals may be unwilling to grant permission to access their camera for capturing user emotions, citing concerns related to privacy issues.

Tegetmeier et al., explored artificial intelligence methods for collaborative book recommender systems, with an emphasis on matrix factorization a method utilizing a stochastic gradient descent algorithm and book-based k-nearest-neighbor approach. The writers carry out a thorough case study using the Book-Crossing benchmark dataset. They investigate several iterations of these AI algorithms to forecast unidentified book ratings and recommend highly regarded books to specific consumers. The objective of this research is to assess the efficacy of different approaches when recommending books by applying particular evaluation measures designed for AI systems. [7]A limitation is that AI algorithms in recommendation systems tend to inundate users with suggestions, even if they simply browsed an item without any intent to purchase.

Guo et al., presented a collaborative filtering recommendation system that was based on emotion and trust. To address sparsity issues, the authors utilized a technique founded on explicit and implicit satisfaction. Additionally, both subjective and objective trust were incorporated to establish trust connections among users, where objective trust was determined by the similarity of conviction, including rating and preference similarity, and subjective trust was based on the six degrees of separation familiarity among users. Furthermore, a target user was provided with a group of trustworthy neighbours derived from the trust connection. To further eliminate malevolent users or attackers from the neighbourhood, the set was subsequently filtered based on user emotional consistency, extracted from implicit user behaviour data, suggested a list of recommendations that was generated for the target user based on evaluations of items by the screened trusted neighbours and the trust ties between the target user and these neighbours. [8] However, this method deals with hurdles when dealing with new users or items with limited interaction data, resulting in the cold start issue.

Ishanka, employed user emotion, behaviour, and personality as contextual parameters for context-aware recommendation in tourist destination suggestion. They utilized a lexicon-based semantic classification method to define emotion tags for each location based on TripAdvisor reviews. Results from tensor factorization showed improved efficacy in destination selection compared to other techniques. Additionally, the study examined how users' emotions influence decision-making processes using Twitter profiles. The focus was on suggesting tourist destinations, highlighting the relevance of considering user behaviour and emotion as contextual criteria in recommendation systems.[2]The possible lack of context sensitivity and a subtle grasp of lexicon-based semantic classification methods for emotion tag definition can lead to inaccurate or oversimplified definitions of the intricacy of human emotions.

3. PROPOSED SYSTEM

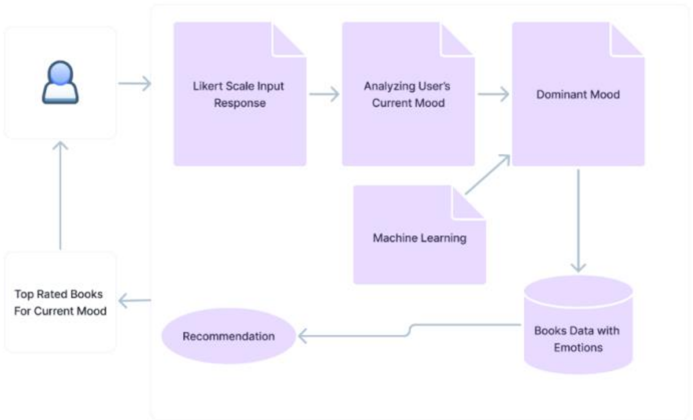

Figure 1: Recommendation System Architecture

This recommendation system is mood-based and operates in real-time as shown in Fig.1. This system functions as the user's own assistant. Since the system is crafted to obtain current mood and make recommendations in real-time, we utilize a mood meter to extract the users' present mood.[6] A Likert scale is used to compute the dominant mood, which aids in identifying the user's dominant emotion. This system distinguishes itself from existing recommendation systems by its emphasis on categorizing recommendations as per individual user's current and predominant mood.[9], [10]

This innovative recommendation system is distinguished by its ability to dynamically adjust book recommendations in accordance with user's prevailing mood. When a user expresses a melancholic mood, characterized by feelings of sadness, our system responds by recommending books known for their inspirational, motivational, and uplifting themes. These recommendations aim to uplift the user's spirits and provide solace during times of emotional distress. Conversely, when a user indicates a joyful disposition, our system employs a unique approach. It curates recommendations by blending books that evoke both happiness and sadness, utilizing randomization techniques to introduce variety and intrigue. This eclectic mix caters to the dynamic nature of human emotions, providing users with wide array of reading preferences that resonate with their current emotional state.[11], [12]

In instances where a user's mood registers as neutral, our system recommends books with themes and narratives that maintain a balanced and impartial tone. These recommendations are carefully curated to align with the user's neutral emotional state, offering content that is neither overly uplifting nor melancholic, but rather conducive to a state of emotional equilibrium.[5], [13] By tailoring recommendations to match the user's emotional context, our recommendation system aims to enrich the reading experience by fostering emotional resonance and connection. This approach emphasizes the commitment in delivering personalized and impactful recommendations that cater to the diverse emotional demands of users.[11]

4. METHODOLOGY

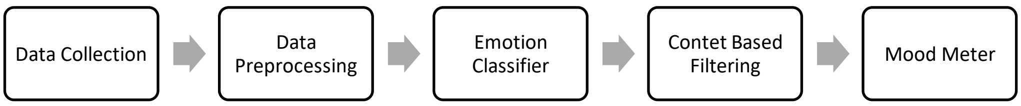

Figure 2: A Step-by-Step Overview of an Inclusive Methodological Flow

4.1 DATA COLLECTION

In Fig.2, this research flow, undertook the task of data collection from the prominent online bookseller, Amazon Books Online, employing web scraped data. The dataset comprises 30,000 meticulously curated entries, each delineated across 12 distinct attributes. These attributes include an identifier (Unnamed: 0), ISBN (International Standard Book Number), rating, book title, author, year of publication, publisher, and image URLs in various sizes (img_s, img_m, img_l) of the book cover. Furthermore, dataset encapsulates a summary of each book's content, denoted by the 'Summary' attribute, alongside language specifications and a novel dimension of emotional classification ('Emotions') pertinent to the books. Each entry is meticulously categorized, enabling comprehensive analysis and exploration of the expansive literary landscape encapsulated within the domain of Amazon Books.

4.2 DATA PREPROCESSING

In preprocessing the data several steps were undertaken to ensure its quality and validity for this research. Firstly, removal of HTML tags from the Summary attribute, which contained textual information as it is web scraped data and is crucial for our analysis. This step aimed to clean the text and eliminate any extraneous markup that might interfere with subsequent processing with the NeatText Python library. Additionally, unwanted columns, identified by the 'Unnamed' attribute, in addition the 'img_s url' and 'img_l url' columns, were dropped from the dataset. These columns were deemed irrelevant to our research objectives and thus were excluded to streamline the dataset and focus our analysis on the most pertinent information. Through these preprocessing steps, we aimed to prepare the data for further exploration and analysis, ensuring its integrity and suitability for our research endeavors.

4.3 EMOTION CLASSIFIER

In an amelioration of personalized mood-based book recommendation system, we incorporated the "michellejieli/emotion_text_classifier" model sourced from the Hugging Face platform. Hugging Face is well known for a wide range of natural language processing (NLP) models and applications, which include translation services and chatbots. It is particularly well-known for its conversational AI capabilities, which let people converse with AI systems in a meaningful and organic way.

The "michellejieli/emotion_text_classifier" model is based on DistilRoBERTa-base transformer architecture, tailored specifically for sentiment analysis tasks. It has been fine-tuned by Michelle Jieli using transcripts from the popular television series "Friends" to classify emotions from textual dialogue, particularly from Netflix shows or movies. This model accurately captures a broad range of emotional states by predicting six main Ekman emotions: surprise, anger, disgust, fear, joy, sadness, and sadness, in addition to a neutral class.

In this recommendation system, we leverage the "emotion_text_classifier" to analyze the summaries of books and extract the predominant emotion conveyed within them. This process involves inputting the textual summary of a book into the model, which then predicts the primary emotion evoked by the content. By associating each book with its predominant emotional tone, our recommendation system can personalize book suggestions based on the emotional preferences of the user.

In our recommendation system, we leverage the "emotion_text_classifier" to analyze the summaries of books and extract the predominant emotion conveyed within them. This process involves inputting the textual summary of a book into the model, which then predicts the primary emotion evoked by the content. By associating each book with its predominant emotional tone, our recommendation system can personalize book suggestions based on the emotional preferences of the user.

```
emotion_classifier('A happy couple who broke up months ago make a pact to pretend to still be together for their annual weeklong vacation with their best friends
[{'label': 'sadness', 'scores': 0.7598185}]
```

```
emotion_classifier('Happy Stories!: Real-Life Inspirational Stories from Around the World That Will Raise Your Happiness Level')
[{'label': 'joy', 'scores': 0.9613327}]
```

```
emotion_classifier('A new thriller by the best-selling author combines suspense with the latest in scientific knowledge')
[{'label': 'neutral', 'scores': 0.79083216}]
```

Figure 2.1: Emotions Predicted for Few Summaries of Books'

Figure 2.1 shows the emotions predicted for some of the book's summaries, and here the term "scores" likely refers to the numerical values or probabilities assigned to every emotional category forecasted by the model for a given input text. These ratings represent the model's confidence or belief in the presence of each emotion in the text. For example, if the model predicts emotions such as happiness, sadness, anger, anxiety, repulsion, surprise, and neutrality, it would assign a rating for each of these categories a score indicating the prospect that the text contains that particular emotion. [4] The scores provide valuable insights for the emotional content of the input text, helping users understand the model's predictions and enabling downstream applications such as sentiment analysis, emotion recognition, or personalized recommendation systems.

4.4 CONTENT BASED FILTERING

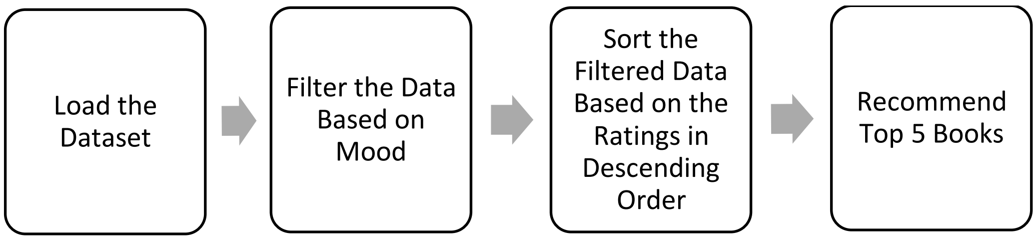

Figure 2.3: A Content Based Filtering workflow

Content-based filtering is an algorithm used for recommending items, such as books, by analyzing their inherent attributes and matching them with the user's preferences. Unlike collaborative filtering, which relies on historical user data, content-based filtering doesn't require past interactions or ratings. Instead, it focuses on the characteristics of the items themselves.[13] Overfitting can sometimes occur in hybrid systems incorporating various recommendation strategies, causing the system to become overly tailored to the training data and perform poorly on new or untested data.

The principle of content-based filtering involves several steps as shown in Fig.2.3. Initially, each book is represented by a set of features extracted from its content. These features encompass various textual elements such as the book's summary, genre, author, language, and keywords. Additionally, in our approach, we incorporated the emotional tone of the book's summary using the "michellejieli/emotion_text_classifier" model.[14], [15] Once the features are extracted, our system computes a similarity score between each book and the user's current dominant mood. This score gauges the likeness between the attributes of the book and the user's emotional preferences. To achieve this, we compare the emotional profile predicted by the "emotion_text_classifier" for each book's summary with the user's dominant mood, derived from real-time data.

Books with the similarity scores that are higher are then recommended to the user, as they are deemed most aligned with the user's current emotional state and preferences. We further tailored our recommendation system to cater to three primary moods: happy, sad, and neutral. By categorizing users' emotional states into these distinct categories, this research aim is to simplify the user experience, ensuring that every user can easily comprehend and engage with the system.

In this refinement, users are prompted to indicate their current mood from among these three options: happy, sad, or neutral. Based on their selection, the system dynamically adjusts its recommendations to align with the corresponding emotional profile.[2], [4], [11] This categorization enables users to effortlessly understand how their mood influences the book recommendations provided by the system. Furthermore, to refine the recommendations, we employ a rating filtering process. This entails selecting only the top-rated books from the subset that matches the user's dominant mood. By prioritizing highly rated books, this paper aims to enhance the quality of the recommendations.

4.5 MOOD METER

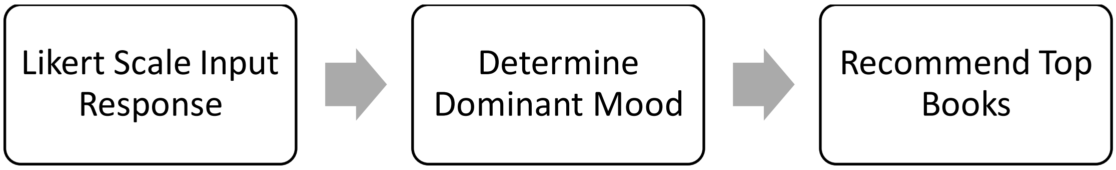

Figure 2.4: The operation flow of a mood meter

In this system we utilize a Likert scale to gauge the user's emotional state. The Likert scale is a widely used psychometric tool that measures attitudes or opinions by asking individuals to indicate their level of agreement or disagreement with a set of statements. It typically consists of several items or questions, each accompanied by a range of response options, typically ranging from strongly disagree to strongly agree. We employ the Likert scale to prompt users to input numeric values corresponding to their responses to lineup of questions aimed at capturing their emotional state dynamically as shown in Fig.2.4. These questions are carefully crafted to elicit meaningful insights into the user's mood, enabling us to discern their dominant emotional disposition.[6], [9]

Once the user provides answers to the Likert scale questions, our system analyzes the aggregated data to identify the prevailing sentiment. This is determined by selecting the emotional category with the highest numerical rating of all responses. Based on the identified prevailing mood, our system then recommends the five books that best match that particular emotional state.

By this we facilitate a structured and standardized approach to capturing user emotions. This enables us to provide personalized book recommendations tailored to the user's prevailing mood, enhancing the meaningfulness and effectiveness of this recommendation system.

5. RESULTS AND DISCUSSION

Figure 3: Integrated Mood Assessment and Book Recommendation System: Final Output

The aforementioned figure 3 displays the customized personalized mood-based book recommendation system's final result. With the use of a Likert scale input, where users rate different emotional states, this system ascertains the dominant mood of the user. The user's predominant mood is then determined by the system's analysis of these ratings. Using Content based filtering the system suggests the best-rated books that suit the user's emotional tastes based on this prevailing mood. Users' reading experiences are improved by this recommendation system, which guarantees that they will receive customized book recommendations based on their present mood.

6. CONCLUSION

In conclusion, our development of the Personalized Mood-Centric Book Recommendation System represents a significant contribution to enhancing Subjective Well-being (SWB) by offering tailored book recommendations to users based on their emotional state. By leveraging a Content-based filtering algorithm, we ensure that users experiencing low moods are provided with uplifting, inspirational, and happy book selections, catering to their emotional needs. Furthermore, our integration of an Emotion Classifier algorithm enables the system to detect and analyze users' emotions accurately. This capability ensures that book recommendations are aligned with the user's current emotional state, thereby maximizing the potential for positive impact on mental health.

Through this innovative approach, our system serves as an effective assistant to users, offering personalized recommendations that not only entertain but also uplift and inspire. By focusing on the user's emotional well-being, this system strives to create a more enriching and fulfilling reading experience, ultimately contributing to overall subjective well-being.

Future research efforts may focus on discerning various user emotions while considering age as a crucial factor. This entails investigating how age influences individuals' emotional responses and perceptions across different contexts. By delving into this aspect, researchers can gain deeper insights into how sentiment analysis can be tailored to cater to diverse age groups, thereby enhancing user experiences and engagement.

REFERENCES

[1] M. Polignano, F. Narducci, M. de Gemmis, and G. Semeraro, “Towards Emotion-aware Recommender Systems: an Affective Coherence Model based on Emotion-driven Behaviors,” *Expert Syst Appl*, vol. 170, May 2021, doi: 10.1016/j.eswa.2020.114382.

[2] S. P. T. Yukawa, “A Context-aware Travel Recommendation System based on User Emotion and Personality UA Piumi Ishanka,” 2018.

[3] A. Mahadik, S. Milgir, V. Bharathi Jagan, V. Kavathekar, and J. Patel, “Mood based Music Recommendation System; Mood based Music Recommendation System.” [Online]. Available: www.ijert.org

[4] K. Anoop, P. Deepak, S. Sam Abraham, V. L. Lajish, and M. P. Gangan, “Readers’ affect: predicting and understanding readers’ emotions with deep learning,” *J Big Data*, vol. 9, no. 1, Dec. 2022, doi: 10.1186/s40537-022-00614-2.

[5] Y. Sbai Idrissi, “The Mood-Genre Confluence: A Framework for Tailored Book Suggestions”, doi: 10.5281/zenodo.8280867.

[6] V. Babanne, M. Borgaonkar, M. Katta, P. Kudale, and V. Deshpande, “EMOTION based PERSONALIZED RECOMMENDATION SYSTEM,” *International Research Journal of Engineering and Technology*, 2020, [Online]. Available: www.irjet.net

[7] C. Tegetmeier, A. Johannssen, and N. Chukhrova, “Artificial Intelligence Algorithms for Collaborative Book Recommender Systems,” *Annals of Data Science*, 2023, doi: 10.1007/s40745-023-00474-4.

[8] L. Guo, J. Liang, Y. Zhu, Y. Luo, L. Sun, and X. Zheng, “Collaborative filtering recommendation based on trust and emotion,” *J Intell Inf Syst*, vol. 53, no. 1, pp. 113–135, Aug. 2019, doi: 10.1007/s10844-018-0517-4.

[9] J. Mumu, B. Tanujaya, R. Charitas, and I. Prahmana, “Likert Scale in Social Sciences Research: Problems and Difficulties,” *FWU Journal of Social Sciences*, vol. 16, no. 4, pp. 89–101, 2022, doi: 10.51709/19951272/Winter2022/7.

[10] A. Saxena, A. Khanna, and D. Gupta, “Emotion Recognition and Detection Methods: A Comprehensive Survey,” *Journal of Artificial Intelligence and Systems*, vol. 2, no. 1, pp. 53–79, 2020, doi: 10.33969/AIS.2020.21005.

[11] R. Rani and R. Sahu, "Book Recommendation Using K-Mean Clustering and Collaborative" Int. J. Eng. Sci. Res. Technol., vol. 6, no. 12, pp. 94–103, 2017.

[12] N. Vaidya and A. R. Khachane, "Recommender Systems - The need of the Ecommerce Era" Proceedings of the IEEE 2017 International Conference on Computing Methodologies and Communication, pp. 100–104, 2017.

[13] K. Tsuji,"Book Recommender System for Wikipedia Article Readers in a University Library" in 2019 8th International Congress on Advanced Applied Informatics, 2019, pp. 121–126, 2019.

[14] X. Wang, F. Luo, C. Sang, J. Zeng, and S. Hirokawa, "Personalized movie recommendation system based on support vector machine and improved particle swarm optimization" IEICE Transactions on Information and Systems, vol. E100-D, no. 2, pp. 285–293, 2017.
[15] K. Priyanka, A. S. Tewari, and A. G. Barman, "Personalised book recommendation system based on opinion mining technique" Global Conference on Communication Technologies, pp. 285–289, 2015.
[16] P. Jomsri, "Book Recommendation System for Digital Library based on User Profiles by using Association Rule" in Fourth edition of the International Conference on the Innovative Computing Technology, pp. 130–134, 2014.
[17] R. Karimi, W. Martin, A. Nanopoulos et al., "Factorized decision trees for active learning in recommender systems," in Proceedings of the IEEE International Conference on Tools with Artificial Intelligence, Herndon, VA, USA, 2013.
[18] U. Liji, Y. Chai, and J. Chen, "Improved personalized recommendation based on user attributes clustering and score matrix filling," Computer Standards & Interfaces, vol. 57, pp. 59–67, 2018
[19] L. Huang, W. Tan, and Y. Sun, "Collaborative recommendation algorithm based on probabilistic matrix factorization in probabilistic latent semantic analysis," Multimedia Tools and Applications, vol. 78, no. 7, pp. 8711–8722, 2019.
[20] Z. Gao, Y. Fan, C. Wu et al., "SeCo-LDA: mining service Co-occurrence topics for composition recommendation," IEEE Transactions on Services Computing, vol. 12, no. 3, pp. 446–459, 2019.

BIOGRAPHIES OF AUTHORS

	**Sarwath Unnisa** – Sarwath Unnisa is an accomplished author and Assistant Professor in the Department of Computer Science at Mount Carmel College, located in Bengaluru, India.With a passion for interdisciplinary research, Sarwath has made significant contributions to various fields within computer science. Her research endeavors have not only contributed to the academic community but have also addressed real-world challenges, fostering innovation and technological advancement. She can be contacted at email: sarwath.unnisamcc@gmail.com
	**Akshaya N S –** Successfully completed BSc. at Maharani Cluster University, Palace Ground, Bengaluru. Currently pursuing MSc degree, Akshaya continues to demonstrate a thirst for knowledge and a commitment to academic rigor. With unwavering dedication, intellectual curiosity, and commitment to excellence, is poised to make significant contributions to both academia and society. She can be contacted at email: aksha7746@gmail.com