MARKS ANALYZER AND COURSE RECOMMENDATION SYSTEM

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Abstract— Online courses have become integral to skill development and education. With a vast array of courses and certifications available on the internet through open learning platforms, learners often struggle to make informed choices without direct expert guidance. This can result in wasting both time and resources on irrelevant courses. In response to this challenge, this paper introduces a machine learning-based solution to recommend suitable courses to learners by leveraging their learning history and past performance.

The proposed framework starts by categorizing new learners into clusters using the k-means clustering algorithm, based on their previous performance. Within each cluster, collaborative filtering is employed to suggest a curated selection of courses that align with their educational goals. Additionally, the framework assesses the adaptability of learners to the recommended courses through online testing, ensuring that the courses are well-suited to their individual needs. Ultimately, this approach aims to create a personalized learning environment for each learner.

I. INTRODUCTION

The main problem for today's learners is that they need tailored access to facts statistics based on preferences and requirements. To address this issue, the recommender system is used to analyse data automatically according to the user preferences. To personalize data, the recommender system is used either to acknowledge a comparable user or to identify specific items of user's concern. (RS) prioritize information, linked to items, and provided users with significant suggestions to their interest. In India, a few online learning platforms or massive open online course (MOOC) like national program on technology enhanced learning (NPTEL), active learning platforms for young aspiring minds (SWAYAM) are developed by the government of India. These (MOOC) can lead the learners to potential carrier failure without proper guidance and irrelevant course chosen by the learners. A CRS may help the student to choose correct courses and the personalized environment will able to engage the learner to the framework. A recommender system is an intelligent system that takes the data of the student whose input is given to the algorithm from the website created .The recommender systems mainly filter the information based on user rating or opinion on some item called collaborative filtering or previous users' choice known as content-based filtering. Content-based filtering recommends the choice opted by some similar person in the past. Clustering is the machine learning technique to classify a data set into a finite number of groups based on similarity among data. These methods are unsupervised learning technique and mainly used for classifying unlabeled historical data. In the classified groups, members in each group are similar to each other and dissimilar to the members of other groups.

II. LITERATURE REVIEW

The Marks Analyzer and Course Recommendation System discussed in this paper has the potential to improve existing systems by addressing the personalization of the learning environment for each course. Previous frameworks have mainly utilized content-based filtering, collaborative filtering, and pattern mining or knowledge mining techniques. For example, Badarenah et al. (2017) proposed an elective course recommender system using rough set theory and clustering algorithms. Ng et al. (2017) focused on topic, sentiment, and tag analysis for course recommendations, but faced challenges in collecting reliable survey data. Bakhshinategh et al. (2017) developed a course recommendation system based on graduate attributes, while Grewal et al. (2016) clustered historical data to recommend courses based on learner's previous knowledge and future interests. Bhumichitr et al. (2017) used correlation coefficient and ALS for elective course recommendations, while Cheng et al. (2018) proposed an ontology-based hybrid system that combines collaborative filtering and content filtering. Additionally, custom algorithms have been proposed for course sequence recommendations, taking into account prerequisites and adaptability to topics. Overall, these studies highlight the importance of recommender systems in enhancing student behavior, achievements, and skill development in online learning environments. However, our proposed framework follows content based recommendations based on keywords and tags. It provides Youtube and Coursera links based on students mark.

III. METHODOLOGY

Data Collection : The data collection is the initial step of research in which the data is collected from the universities database. The dataset had 50 student records.

Design Data Structure:

- Design a data structure to store student information, including usernames, passwords, and academic performance.
- Choose a suitable data structure based on your programming language and requirements

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1. **Data Collection:**
   Collect data for a sample set of students, including their marks, usernames, and passwords.
2. **Authentication System:**
   Implement a secure authentication system to verify usernames and passwords.
   Incorporate password hashing for security.

3. **Home Page:**
   Create a "Home" page with a login form for existing users.
   Include a registration form for new users to create accounts.
4. **Result Page:**
   Design a "Result" page to display student information and academic performance.
   Implement the logic for fetching and displaying marks.
5. **Marks Analysis:**
   Develop algorithms to analyze marks, and provide insights into subject-wise performance.
   Display the analysis results on the "Result" page.
6. **Content-Based Recommendations:**
   Identify subjects with marks below 50.
   Implement content-based recommendation logic based on the identified subjects.
   Display recommended content links on the "Result" page.
7. **Security Measures:**
   Ensure the security of user credentials through proper authentication mechanisms.
   Use HTTPS for secure communication if your application is web-based.
8. **User Interface Design:**
   Design a user-friendly interface for both the "Home" and "Result" pages.
   Consider responsiveness for different devices.
9. **Testing:**
   Test the system thoroughly to identify and fix bugs.
   Perform security testing to ensure the system is resilient to common vulnerabilities.
10. **Optimization:**
    Optimize the code for performance.
    Consider caching strategies if applicable.
11. **Documentation:**
    Document the code, including comments for better understanding.
    Create user documentation to guide students on how to use the system.
12. **Deployment:**
    Deploy the application on a suitable platform, whether it's a web server or a cloud service.
13. **Monitoring and Maintenance:**
    Set up monitoring tools to keep track of system performance.
    Plan for regular maintenance and updates as needed.

Content-based Recommendations: A recommender system based on content makes use of the data provided by the user either explicitly (marks, preferences, rating) or implicitly (keywords, tags).A User profile is crated based on that data, which is used to make recommendations to the user. Term Frequency (TF) and Inverse Document Frequency (IDF) are widely used to determine a particular article's / document's/ course's/ movie's/ news item's etc. relative importance. TF is the occurrence of a word in a document and IDF is the logarithmic inverse of the document frequency among the whole corpus of documents. For example, if we search for "the use of recommender system" on a search engine. It is expected that 'the' will have higher frequency that 'recommender' in the corpus. But, 'recommender' is the most important part for the search query. In such situation the TF-IDF ignores the effect of unimportant high frequency words. In TF-IDF, log is used to reduce the effect of high frequency words.

IV.CONCLUSION

Recommender systems made significant progress over the last decade when numerous content-based, collaborative, 746 IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING, VOL. 17, NO. 6, JUNE 2005 and hybrid methods were proposed and several "industrial-strength" systems have been developed. However, despite all of these advances, the current generation of recommender systems surveyed in this paper still requires further improvements to make recommendation methods more effective in a broader range of applications. In this paper, we reviewed various limitations of the current recommendation methods and discussed possible extensions that can provide better recommendation capabilities. These extensions include, among others, the improved modeling of users and items, incorporation of the contextual information into the recommendation process, support for multcriteria ratings, and provision of a more flexible and less intrusive recommendation process. We hope that the issues presented in this paper will advance the discussion in the recommender systems community about the next generation of recommendation technologies.

V.REFRENCES

[1] B. Mondal, Artificial Intelligence: State of the Art. Cham: Springer International Publishing, 2020, pp. 389–425. [Online]. Available: https://doi.org/10.1007/978-3-030-32644-9-32

[2] F. Isinkaye, Y. Folajimi, and B. Ojokoh, "Recommendation systems: Principles, methods and evaluation," Egyptian Informatics Journal, vol. 16, no. 3, pp. 261–273, 2015.

[3] N. Pritam, M. Khari, L. Hoang Son, R. Kumar, S. Jha, I. Priyadarshini, M. Abdel-Basset, and H. Viet Long, "Assessment of code smell for predicting class change proneness using machine learning," IEEE Access, vol. 7, pp. 37 414–37 425, 2019.

[4] B. Mondal and J. P. Choudhury, "A comparative study on k means and pam algorithm using physical characters of different varieties of mango in india," International Journal of Computer Applications, vol. 78, no. 5, 2013.

[5] M. R. McLaughlin and J. L. Herlocker, "A collaborative filtering algorithm and evaluation metric that accurately model the user experience," in Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval. ACM, 2004, pp. 329–336.

[6] L. Esmaeili, M. Nasiri, and B. Minaei-Bidgoli, "Personalizing group recommendation to social network users," in International Conference

on Web Information Systems and Mining. Springer, 2011, pp. 124–133.

[7] A. Al-Badarenah and J. Alsakran, "An automated recommender system for course selection."

[8] Y. Ng and J. Linn, "Crsrecs: A personalized course recommendation system for college students," in 2017 8th International Conference on Information, Intelligence, Systems Applications (IISA), Aug 2017, pp. 1–6.

[9] G. DS and K. K, "Developing an intelligent recommendation system for course selection by students for graduate courses," Business and Economics Journal, vol. 7, no. 2, pp. 1–9, 2016. [Online]. Available: https://www.omicsonline.org/open-access/developing-anintelligent-recommendation-system-for-course-selectionby-students-forgraduate-courses-2151-6219-1000209.php?aid=73333

[10] K. Bhumichitr, S. Channarukul, N. Saejiem, R. Jiamthapthaksin, and K. Nongpong, "Recommender systems for university elective course recommendation," in 2017 14th International Joint Conference on Computer Science and Software Engineering (JCSSE), July 2017, pp. 1–5.

[11] J. Lin, H. Pu, Y. Li, and J. Lian, "Intelligent recommendation system for course selection in smart education," Procedia Computer Science, vol. 129, pp. 449 – 453, 2018, 2017 INTERNATIONAL CONFERENCE ON IDENTIFICATION,INFORMATION AND KNOWLEDGEIN THE INTERNET OF THINGS. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1877050918302424