Ahliya Journal of Business Technology and MEAN Economies
[Published by Palestine Ahliya University]
Vol. 02 Issue 01 (2025)
ISSN: 3007-9691

Recommender System for Smart University Registration System

Majdi A. Daajneh[1], Jamil Itmazi[2]
[1] Palestine Ahliya University (Palestine)
✉ majdi@paluniv.edu.ps
[2] Associate Professor, Palestine Ahliya University (Palestine)
✉ j.itmazi@paluniv.edu.ps

Received:29/04/2025 Accepted:25/05/2025 Published:31/05/2025

Abstract:

Recommender Systems (RSs) have gained significant traction across industries such as e-commerce and digital media; however, their use in academic course recommendation remains relatively underdeveloped. This paper explores the design and implementation of a RS tailored for a smart university registration system, with the goal of streamlining the course selection process for undergraduate students. By analysing similarities in academic plans, the system delivers personalized course suggestions, facilitating smoother pre-registration and enriching the academic journey. It employs a combination of collaborative filtering, content-based filtering, and hybrid techniques to generate precise and relevant recommendations. Designed for seamless integration with existing university infrastructure, the system prioritizes scalability, ease of use, and ethical data practices. Its adoption is expected to enhance student satisfaction, retention, and academic success, while also alleviating the burden on academic advisors and administrative personnel. The research addresses key challenges including data availability, interface usability, and integration complexity, offering practical advancements in the realm of educational technology.

Keywords: *Recommender Systems; University Courses; Smart University System; Collaborative Filtering; Content-Based Filtering; Educational Technology.*

Ahliya Journal of Business Technology and MEAN Economies [Published by Palestine Ahliya University]
Vol. 02 Issue 01 (2025) ISSN: 3007-9691

نظام التوصية لنظام التسجيل الذكي في الجامعات

مجدي دعاجنة[1]، جميل اطميزي[2]

[1] جامعة فلسطين الأهلية (فلسطين)
majdi@paluniv.edu.ps
[2] أستاذ مشارك، جامعة فلسطين الأهلية (فلسطين)
j.itmazi@paluniv.edu.ps

تاريخ الاستلام:2025/04/29 تاريخ القبول:2025/05/25 تاريخ النشر:2025/05/31

ملخص:

اكتسبت أنظمة التوصية (RS) زخمًا كبيرًا في قطاعات مثل التجارة الإلكترونية والوسائط الرقمية؛ إلا أن استخدامها في التوصية بالمقررات الأكاديمية لا يزال غير متطور نسبيًا، تستكشف هذه الدراسة تصميم وتنفيذ نظام توصية مُصمم خصيصًا لنظام تسجيل جامعي ذكي، بهدف تبسيط عملية اختيار المقررات الدراسية لطلاب البكالوريوس، من خلال تحليل أوجه التشابه في الخطط الأكاديمية، يُقدّم النظام اقتراحات مُخصصة للمقررات الدراسية، مما يُسهّل عملية التسجيل المسبق ويُثري المسيرة الأكاديمية. يستخدم النظام مزيجًا من التصفية التعاونية والتصفية القائمة على المحتوى والتقنيات الهجينة لإنشاء توصيات دقيقة ومناسبة. صُمم النظام للتكامل السلس مع البنية التحتية الجامعية الحالية، ويُولي الأولوية لقابلية التوسع وسهولة الاستخدام وممارسات البيانات الأخلاقية. من المتوقع أن يُعزز اعتماده رضا الطلاب ونجاحهم الأكاديمي، مع تخفيف العبء على المُرشدين الأكاديميين والموظفين الإداريين. تتناول الدراسة التحديات الرئيسية، بما في ذلك توفر البيانات، وسهولة استخدام الواجهة، وتعقيد التكامل، مُقدمًا تقدمًا عمليًا في مجال تكنولوجيا التعليم.

الكلمات المفتاحية: *أنظمة التوصية؛ المقررات الجامعية؛ نظام الجامعة الذكي؛ التصفية التعاونية؛ التصفية المعتمدة على المحتوى؛ التكنولوجيا التعليمية.*

1. Introduction

Recommender Systems (RSs) simplify decision-making by offering personalized suggestions in e-commerce, entertainment, and hospitality (Ricci et al., 2021). In smart universities, RSs can streamline course selection, reducing time spent evaluating options while aiding advisors in section recommendations (Ricci et al., 2010).

RSs use filtering techniques like:

- Collaborative filtering (user similarity) (Williams et al., 2021).
- Content-based filtering (item attributes) (Tewari, 2020).
- Hybrid methods (combined accuracy) (Alhammadi et al., 2016).
- Demographic-based (user traits) (Olsson, 2003).

Benefits include:

- Enhanced engagement via tailored suggestions (Pu & Chen, 2006).
- Higher revenue through targeted recommendations (Kumar et al., 2024).
- Improved retention in education (Haktanır, 2020).
- Challenges include privacy risks and algorithmic bias. In smart universities, RSs can personalize course selection, advising, and research collaboration while ensuring ethical data use (Fan et al., 2022).

1.1 Problem statement:

Many students face difficulties selecting suitable courses and sections during pre-registration, delaying their academic progress and potentially affecting graduation timelines. Without an intelligent system, students must manually navigate complex course catalogs and schedules to align choices with their academic plans.

The core challenge is developing a system that:

- Recommends optimal courses and sections based on academic plans, major requirements, prerequisites, and schedule availability.

Key development challenges include:

- Data availability: Accessing and analyzing course data (prerequisites, availability) for accurate recommendations.
- User interface: Ensuring an intuitive interface for easy input of preferences and retrieval of recommendations.
- System integration: Seamlessly connecting with university systems (e.g., student information, course catalogs) for real-time data.
- Scalability: Supporting large student/course volumes and adapting to catalog changes.

The goal is to create a scalable RS that delivers precise course recommendations while addressing data, usability, integration, and scalability hurdles.

1.2 Research Questions

The study will address the following questions:

- How can a recommender system be designed to suggest personalized course recommendations to students within the Smart University System?
- What factors should be considered in the development of the recommender system, such as student preferences, academic history, and major requirements?
- How effective is the recommender system in improving student course selection and academic performance?

1.3 Objective of the study

The research aims to propose RSs for smart university systems. Specifically, our study focuses on developing a RS to help students choose courses and their sections based on their academic plan.

The proposed RS in this research is designed to help students register effectively and quickly based on the courses offered and their academic plans, which the RS considers an essential component of the smart university system, providing personalized recommendations to students and faculty members based on their preferences, interests, and past performance.

1.4 Significance of the study

The RS is vital for smart universities due to:

- Personalization: Offers tailored course and scheduling recommendations, enhancing student/faculty experience (Meddeb et al., 2021).
- Efficiency: Streamlines tasks like course selection, saving time and resources.
- Improved Retention: Suggests courses aligned with student interests, boosting engagement (Jing, 2024).
- Better Advising: Provides data-driven guidance, improving academic outcomes (Ganeshan & Li, 2015).
- Data Insights: Reveals user preferences to enhance system functionality (Meddeb et al., 2021).
- A smart university RS also:
- Increases student satisfaction and autonomy.
- Reduces advisor workload.
- Enhances graduation rates and post-grad opportunities.
- Improves administrative efficiency (Meddeb et al., 2021; Ganeshan & Li, 2015; Jing, 2024).
- RSs in higher education boost engagement and academic success (Meddeb et al., 2021).

2. Background Theory

The explosion of internet users in the 1990s led to a data overload, making it difficult for users to find relevant information (Du et al., 2016). This challenge also presented opportunities for businesses to leverage online spaces for promotion and sales (Cho et al., 2007). However, linguistic variability, slang, and polysemous words further complicated online searches. Social media conversations, for instance, rarely match the clarity and quality of scientific articles, emphasizing the need for tools like artificial intelligence and recommender systems (Benfares et al., 2017).

2.1 Recommender Systems

Karlgren (1990) introduced recommender systems, which predict user preferences by analyzing large datasets (Mrhar & Abik, 2019). As internet usage expanded, recommender systems evolved from e-commerce to social networks (Dennouni et al., 2018), employing techniques like collaborative, content-based, and hybrid filtering.

In a smart university, each student’s profile—considering preferences like building, days, times, teachers, and credit hours—guides course recommendations. Supervisors can further prioritize courses based on academic plans. Recommendations also consider peer feedback, academic history, career goals, and budgets, supporting informed decision-making.

After gathering data, the system checks if students have completed their guidance plans, suggesting appropriate courses accordingly. Courses are prioritized by supervisor recommendations, specialization relevance, college requirements, and general university courses. Scheduling factors like prerequisites, conflicts, and student preferences are dynamically managed for optimized learning paths.

2.2 The SmartC Software Architecture

SmartC provides a service framework for implementing various recommender systems (Da Silva Lopes et al., 2022). Its architecture consists of three layers: the access environment (user interaction), recommendation management (developer access and processing), and long-term persistence (data storage).

The recommendation engine uses a hybrid approach, alternating between content-based and collaborative filtering (Maruyama et al., 2023).

- Collaborative filtering suggests items based on user behavior similarities (Gm et al., 2024; Zheng et al., 2020), but can suffer from scalability and cold-start issues. Techniques like clustering, SVD (Singular Value Decomposition), and PMF (Probabilistic Matrix Factorization) help mitigate these challenges (Gm et al., 2024). Collaborative filtering is divided into user-based and item-based approaches (Thannimalai & Zhang, 2021; Valdiviezo-Diaz et al., 2019).
- Content-based filtering recommends items similar to those a user previously liked, using keyword extraction like bag-of-words to identify relevant content features (Thannimalai & Zhang, 2021; Eliyas & Ranjana, 2022).
- Hybrid filtering combines both methods for more accurate results (Baidada et al., 2022), while reinforcement learning adapts through user feedback over time (Den Hengst et al., 2020).

Incorporating these approaches, smart university systems can provide personalized, dynamic recommendations, enhancing students' academic journeys.

3. Literature Review

This chapter reviews studies related to recommender systems (RS) and smart universities.

3.1 Previous Studies

Course RSs have diversified into content-based, collaborative-filtering, hybrid, and popularity-based systems. Warnes and Smirnov (2020) proposed a conformal prediction-based RS for reliable course recommendations. In education, data analytics—particularly learning analytics—has surged, focusing on predicting student performance (Ferguson, 2019).

Bhumichitr et al. (2017) developed a course RS comparing Pearson Correlation and Alternating Least Square (ALS) methods, finding ALS achieved 86% accuracy. Despite advancements, many methods struggle with course-specific variations and limited assistance in educational decision-making.

Gulzar et al. (2018) introduced a hybrid RS integrating ontology for personalized course recommendations, improving learner satisfaction and outcomes. Villegas-Ch and García-Ortiz (2023) proposed an ontology-based RS for e-learning, though it faced cold-start challenges.

Arık et al. (2021) created a hybrid RS leveraging professor ratings, enhancing e-learning customization. Machine learning's independent evolution, noted by Warnes and Smirnov (2020), offers hybrid solutions, though confidence in recommendation quality remains limited.

Project-based and non-formal learning contexts benefit significantly from RSs, helping students select courses before registration (Alfaro et al., 2019). Other notable works include:

- Elahi et al. (2022): A hybrid RS improving student engagement.
- Mihaescu et al. (2015): Intelligent tutoring RS enhancing computer science students' performance.
- Althbiti et al. (2021): Personalized RS for academic advising.
- Samin & Azim (2019): RS aiding informed course selection.
- Gm et al. (2024): Academic resource RS improving access to educational materials.
- Bin et al. (2024): Web-based curriculum RS enhancing course planning.

– Urdaneta-Ponte et al. (2021): RS promoting extracurricular activity participation and well-being.

Overall, RSs have shown positive impacts on personalization, advising, and collaboration in higher education. See Table 1.

Table 1: Summary of previous studies related to the study

Author(s)	**Year**	**Contribution**	**Techniques**	**Performance**
Bin et al.	2024	Personalized course planning	Web-based RS	Effective planning
Gm et al.	2024	Educational content RS	Knowledge graphs & cosine similarity	Enhanced recommendations
Althbiti et al.	2021	Academic advising RS	ML & graph analysis	Outperformed traditional models
Urdaneta-Ponte et al.	2021	Graduate course selection RS	Clustering approach	High satisfaction
Elahi et al.	2018	University RS	Hybrid filtering	Improved personalization
Mihaescu et al.	2015	Intelligent tutoring RS	Tutoring system	Positive outcomes

3.2 Comment About Previous Studies

Previous research highlights RSs' ability to save time and enhance efficiency in smart universities. However, most systems struggle with achieving high accuracy, necessitating more advanced algorithms.

This study proposes an evaluation using a randomized controlled trial (RCT) to assess RS impact on students and faculty, featuring:

– Advanced Algorithms: Integration of collaborative, content-based, and hybrid filtering optimized for university data.
– Thorough Data Analysis: Comprehensive review of academic records, registrations, and feedback.
– User-Centric Design: Ensuring recommendations are relevant and actionable, continuously improved via feedback.
– Stringent Assessment: Measuring accuracy, precision, recall, and satisfaction using RCT for robust evidence.

Through these methods, the study aims to enhance RS performance and further improve smart university systems.

4. Methodology

This part outlines the dataset, preprocessing steps, and KNN-based recommender system for course selection in Palestinian universities (Bethlehem University, Al-Quds Open University, Palestine Ahliya University).

4.1 Dataset & Preprocessing

– Data Collection: Surveys and university records from 381 students/staff (by using Krejcie and Morgan table) captured demographics, preferences, and academic performance.
– Features: 15 key attributes (e.g., Student_avg, Course_time, Student_building) mapped numerically via Label Encoder (Table 2).

Table 2. Label encoding conversions.

Feature Name	Feature Labels Map
Student_status_b	No (0), Yes (1)
Student_time_b	Morning (0), Afternoon (1)
Student_days_b	Saturday (0.000000), Saturday (0.166667), etc.
Course_building_b	A (0.00), B (0.20), etc.

- Normalization: MinMaxScaler applied the following equation to scale values [0, 1].

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where:

- ✓ X is the original value.
- ✓ X_{min} is the minimum value in the feature.
- ✓ X_{max} is the maximum value in the feature.
- ✓ X_{scaled} is the normalized value, scaled between 0 and 1.
- Split: 80:20 train-test ratio.

4.2 Research Design

Objectives:

- Optimize course recommendations using student/supervisor profiles.
- Evaluate system impact on academic outcomes.

Methods:

- Mixed-methods: Quantitative (KNN, accuracy metrics) + qualitative (user feedback).
- Ethics: Anonymized data, informed consent, secure storage.

System Workflow

- Student Flow: Recommends courses/sections based on level, unfinished prerequisites, and preferences (hours/days/building/teacher).
- Supervisor Flow: Prioritizes courses aligned with academic plans (Figures 1–3).

Model Performance

- Decision Tree: 90% test accuracy; depth increases improved generalization (Figure 4).
- Gaussian Naive Bayes: 99.09% test accuracy; robust generalization (Figure 5).
- SVM: Overfit (100% training, 10.68% test accuracy) (Figure 6).
- Logistic Regression: 95.23% test accuracy; balanced performance (Figure 7).
- XGBoost: Low log loss (~20 epochs), stable generalization (Figure 8).
- Random Forest: Near 100% accuracy; minimal overfitting (Figure 9).

Tools

- Platform: Integrated RS with CMS/SIS.
- Survey: Captured preferences, satisfaction.
- Analysis: SPSS/R for statistical evaluation.

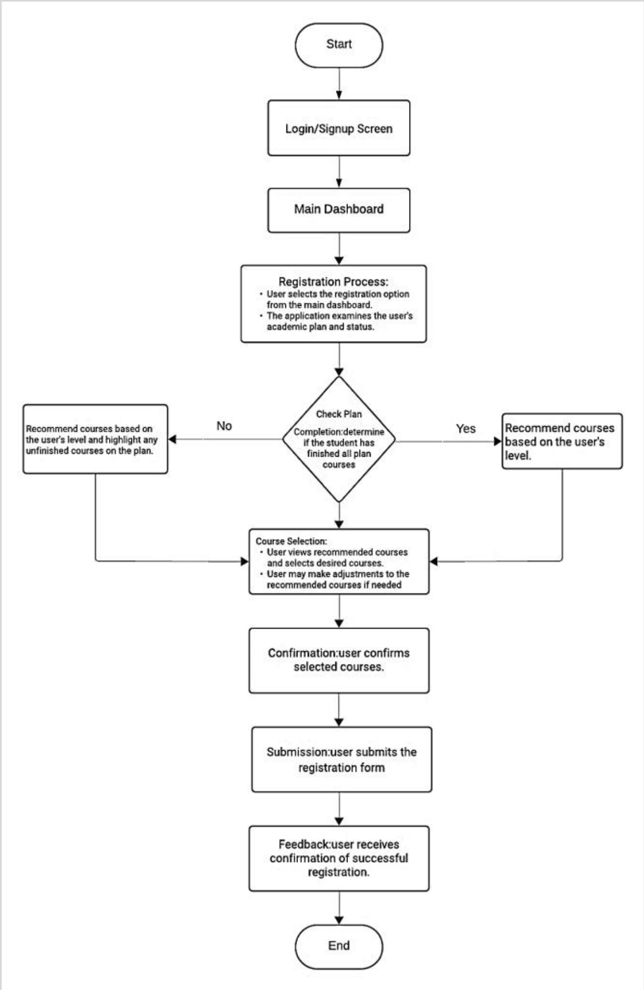

Figure 1: Recommender System Flowchart

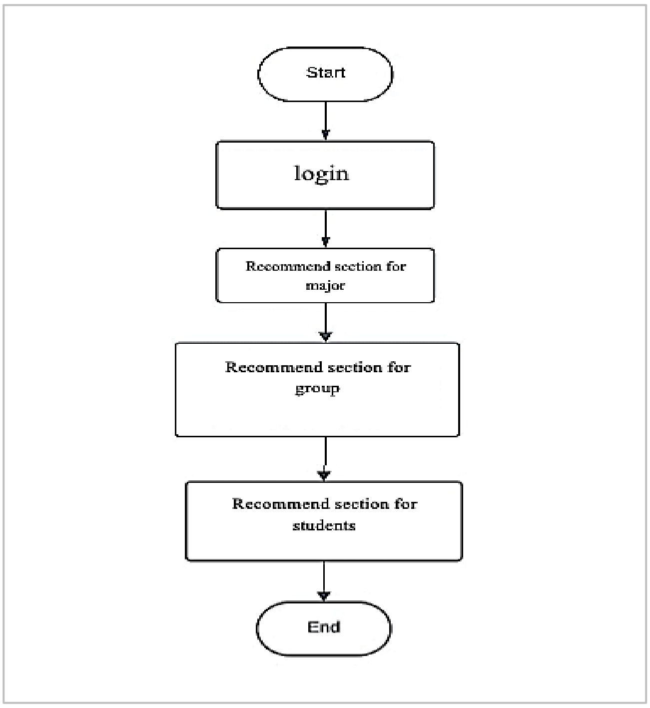

Figure 2: supervisor recommender System Flowchart

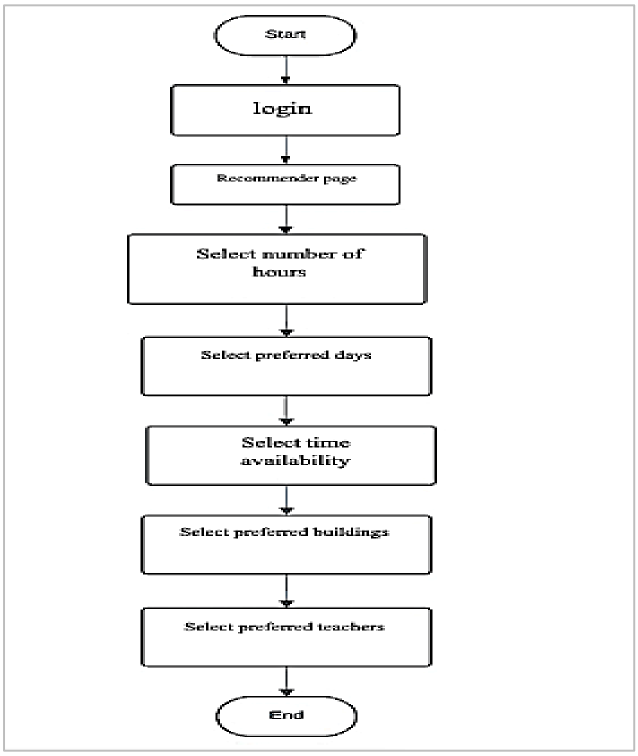

Figure 3: student recommender System Flowchart

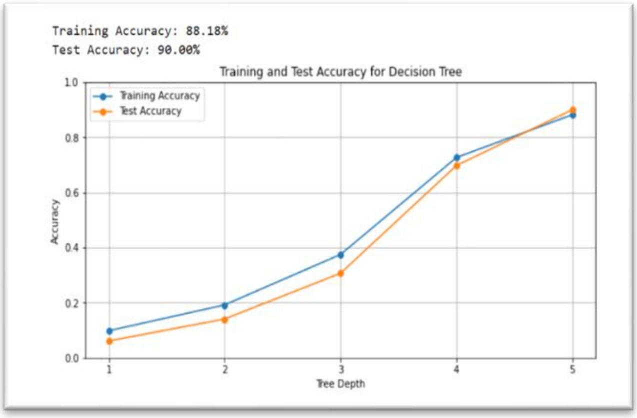

Figure 4: Training and Test Accuracy for Decision Tree

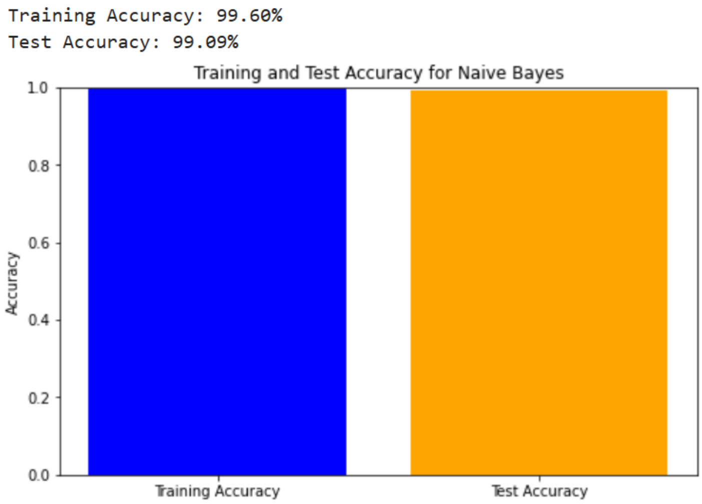

Figure 5: Training and Test Accuracy for Naive Bayes

Figure 6: Training and Test Accuracy for SVM

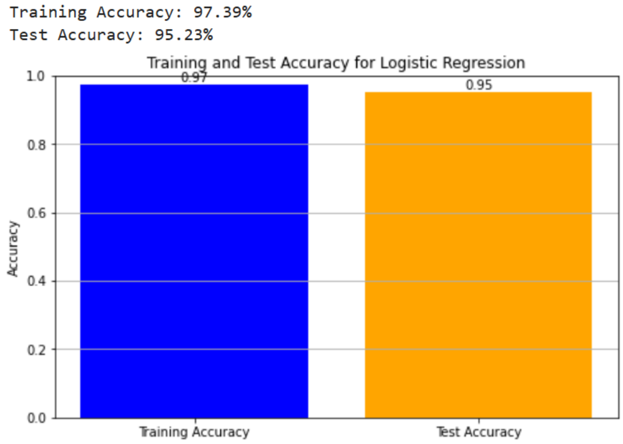

Figure 7: Training and Test Accuracy for Logistic Regression

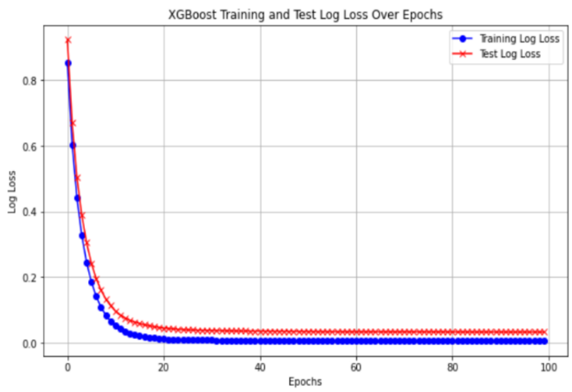

Figure 8: XGBoost Training and Test Log Loss Over Epochs

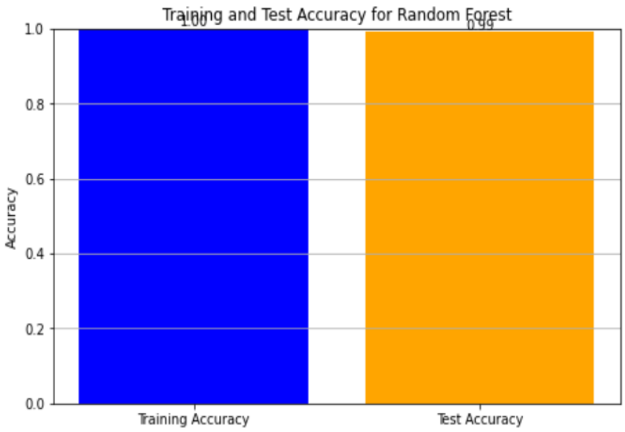

Figure 9: Training and Test Accuracy for Random Forest

5. Discussion & Results

5.1 Key Findings

- Model Performance: XGBoost achieved the highest accuracy (Figure 10), excelling in handling complex student-course interactions. Random Forest followed closely, while SVM underperformed due to overfitting.

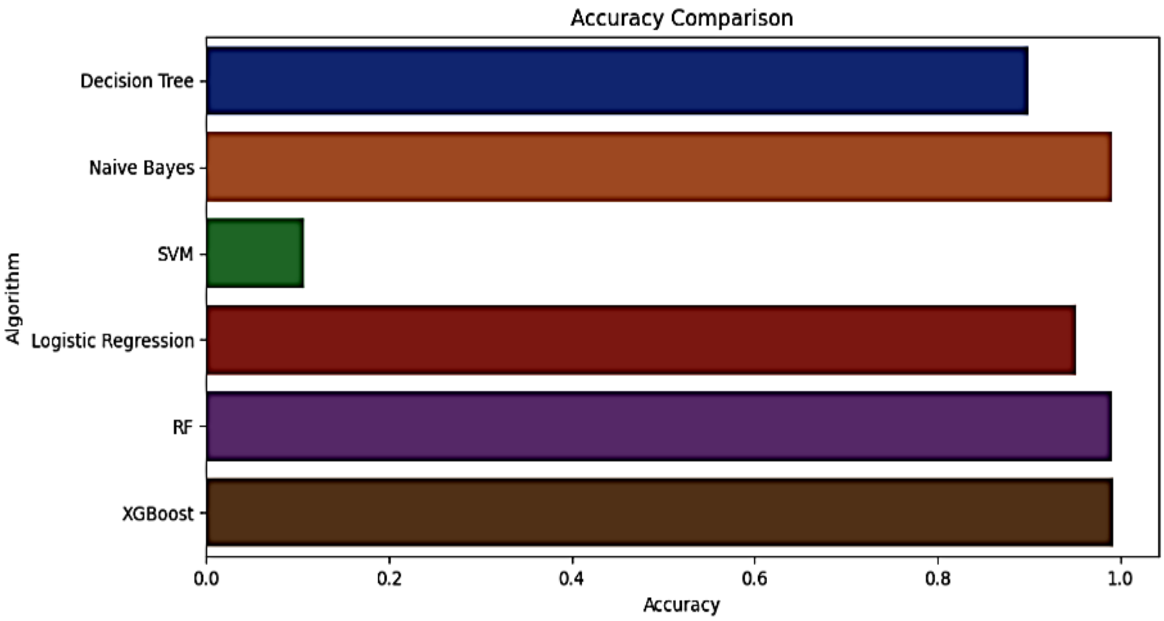

Figure 10: Accuracy Comparison

- Student-Centric Recommendations: The system prioritized courses based on:

1. Supervisor input.
2. Specialization alignment.
3. Student preferences (building, days, time, teacher).

- Conflict-Free Scheduling: Iterative division selection ensured no timetable clashes.

5.2 Implications

- Ensemble Methods: XGBoost/Random Forest outperformed simpler models (Logistic Regression, Naive Bayes) due to their ability to capture non-linear patterns.
- Beyond Accuracy: Future work should incorporate precision, diversity metrics, and real-time feedback to enhance personalization.

6. Future Work

- Advanced Personalization: Integrate learning styles/career goals.
- Predictive Analytics: Forecast course demand.
- Gamification: Boost engagement via badges/rewards.
- Emerging Tech: Explore blockchain (credentials) and AR (course previews).
- Accessibility: Ensure ADA compliance (screen readers, alternative inputs).

References

Alfaro, L., Rivera, C., & Luna-Urquizo, J. (2019). Using Project-based learning in a Hybrid e-Learning system model. *International Journal of Advanced Computer Science and Applications*, *10*(10).

Alhammadi, A., Fadlee, M., & Alraih, S. (2016, May). Effects of different types of RSS data on the system accuracy of indoor localization system. In *2016 IEEE Region 10 Symposium (TENSYMP)* (pp. 311-314). IEEE.

Althbiti, A., Algarni, S., Alghamdi, T., & Ma, X. (2021, March). A Personalized Academic Advisory Recommender System (PAARS): A Case Study. In *2021 4th International Conference on Information and Computer Technologies (ICICT)* (pp. 270-278). IEEE.

Arık, A., Okyay, S., & Adar, N. (2021). Hybrid course recommendation system design for a real-time student automation application. *Avrupa Bilim ve Teknoloji Dergisi*, (26), 85-90.

Baidada, M., Mansouri, K., & Poirier, F. (2022). Hybrid filtering recommendation system in an educational context: experiment in higher education in Morocco. *International Journal of Web-Based Learning and Teaching Technologies (IJWLTT)*, *17*(1), 1-17.

Benfares, C., El Bouzekri El Idrissi, Y., & Abouabdellah, A. (2017, March). Recommendation semantic of services in smart city. In *Proceedings of the 2nd international conference on big data, cloud and applications* (pp. 1-6).

Bhumichitr, K., Channarukul, S., Saejiem, N., Jiamthapthaksin, R., & Nongpong, K. (2017, July). Recommender Systems for university elective course recommendation. In *2017 14th international joint conference on computer science and software engineering (JCSSE)* (pp. 1-5). IEEE.

Bin, Q., Zuhairi, M. F., & Morcos, J. (2024). A comprehensive study on personalized learning recommendation in e-learning system. *IEEE Access*.

Cho, D. Y., Kwon, H. J., & Lee, H. Y. (2007, January). Analysis of trust in internet and mobile commerce adoption. In *2007 40th Annual Hawaii International Conference on System Sciences (HICSS'07)* (pp. 50-50). IEEE.

Da Silva Lopes, A., do Nascimento, A. V. L., da Rosa Floripes, C. R., Maruyama, M. H. M., Lunardi, G. M., & Maran, V. (2022). SmartUFSM: Uma Arquitetura de Software para Suporte a Recomendaçoes em Campus Universitários Inteligentes. *Cadernos de Informática*, *11*(1), 9-26.

Den Hengst, F., Grua, E. M., el Hassouni, A., & Hoogendoorn, M. (2020). Reinforcement learning for personalization: A systematic literature review. *Data Science*, *3*(2), 107-147.

Dennouni, N., Peter, Y., Lancieri, L., & Slama, Z. (2018). Towards an incremental recommendation of POIs for mobile tourists without profiles. *Int. J. Intell. Syst. Appl.(IJISA)*, *10*(10), 42-52.

Du, S., Meng, F., & Gao, B. (2016, December). Research on the application system of smart campus in the context of smart city. In *2016 8th International Conference on Information Technology in Medicine and Education (ITME)* (pp. 714-718). IEEE.

Elahi, M., Starke, A., El Ioini, N., Lambrix, A. A., & Trattner, C. (2022). Developing and evaluating a university recommender system. *Frontiers in Artificial Intelligence*, *4*, 796268.

Eliyas, S., & Ranjana, P. (2022, April). Recommendation systems: Content-based filtering vs collaborative filtering. In *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)* (pp. 1360-1365). IEEE.

Fan, W., Zhao, X., Chen, X., Su, J., Gao, J., Wang, L., ... & Li, Q. (2022). A comprehensive survey on trustworthy recommender systems. *arXiv preprint arXiv:2209.10117*.

Ferguson, R. (2019). Ethical Challenges for Learning Analytics. *Journal of Learning Analytics, 6*(3), 25-30.

Ganeshan, K., & Li, X. (2015, October). An intelligent student advising system using collaborative filtering. In *2015 IEEE Frontiers in Education Conference (FIE)* (pp. 1-8). IEEE.

Gm, D., Goudar, R. H., Kulkarni, A. A., Rathod, V. N., & Hukkeri, G. S. (2024). A digital recommendation system for personalized learning to enhance online education: A review. *IEEE Access*, *12*, 34019-34041.

Gulzar, Z., Leema, A. A., & Deepak, G. (2018). Pcrs: Personalized course recommender system based on hybrid approach. *Procedia Computer Science*, *125*, 518-524.

Haktanır, E. (2020). Interval valued pythagorean fuzzy aggregation operators based malcolm baldrige national quality award assessment. *Journal of Intelligent & Fuzzy Systems, 39*(5), 6431-6441.

Jing, J. (2024, October). Personalized Recommendation of Education Resources Based on K-Means Clustering. In *First International Conference on Real Time Intelligent Systems* (pp. 451-462). Cham: Springer Nature Switzerland.

Karlgren, J. (1990). An algebra for recommendations: Using reader data as a basis for measuring document proximity.

Kumar, A., Sharma, G., Sharma, A., Chopra, P., & Rattan, P. (2024). Advances in Networks Intelligence and Computing. *Intelligence and Computing*.

Maruyama, M. H. M., Silveira, L. W., de Oliveira, J. P. M., Gasparini, I., & Maran, V. (2023). Hybrid Recommender System for Educational Resources to the Smart University Campus Domain. In *CSEDU (1)* (pp. 47-56).

Meddeb, O., Maraoui, M., & Zrigui, M. (2021). Personalized smart learning recommendation system for Arabic users in smart campus. *International Journal of Web-Based Learning and Teaching Technologies (IJWLTT)*, *16*(6), 1-21.

Mihaescu, M. C., Popescu, P. S., & Ionascu, C. M. (2015). Intelligent Tutor Recommender System for On-Line Educational Environments. In *EDM* (pp. 516-519).

Mrhar, K., & Abik, M. (2019, October). Toward a deep recommender system for MOOCs platforms. In *Proceedings of the 3rd International Conference on Advances in Artificial Intelligence* (pp. 173-177).

Olsson, T. (2003). *Bootstrapping and decentralizing recommender systems* (Doctoral dissertation, Uppsala University).

Pu, P., & Chen, L. (2006, January). Trust building with explanation interfaces. In *Proceedings of the 11th international conference on Intelligent user interfaces* (pp. 93-100).

Ricci, F., Rokach, L., & Shapira, B. (2010). Introduction to recommender systems handbook. In *Recommender systems handbook* (pp. 1-35). Boston, MA: springer US.

Ricci, F., Rokach, L., & Shapira, B. (2021). Recommender systems: Techniques, applications, and challenges. *Recommender systems handbook*, 1-35.

Samin, H., & Azim, T. (2019). Knowledge based recommender system for academia using machine learning: a case study on higher education landscape of Pakistan. *IEEE Access*, *7*, 67081-67093.

Tewari, A. S. (2020). Generating items recommendations by fusing content and user-item based collaborative filtering. *Procedia Computer Science*, *167*, 1934-1940.

Thannimalai, V., & Zhang, L. (2021, December). A content based and collaborative filtering recommender system. In *2021 International Conference on Machine Learning and Cybernetics (ICMLC)* (pp. 1-7). IEEE.

Urdaneta-Ponte, M. C., Mendez-Zorrilla, A., & Oleagordia-Ruiz, I. (2021). Recommendation systems for education: Systematic review. *Electronics*, *10*(14), 1611.

Valdiviezo-Diaz, P., Ortega, F., Cobos, E., & Lara-Cabrera, R. (2019). A collaborative filtering approach based on Naïve Bayes classifier. *IEEE Access*, *7*, 108581-108592.

Villegas-Ch, W., & García-Ortiz, J. (2023). Enhancing learning personalization in educational environments through ontology-based knowledge representation. *Computers*, *12*(10), 199.

Warnes, Z., & Smirnov, E. (2020). Course Recommender Systems with Statistical Confidence. *International Educational Data Mining Society*.

Williams, M. T., Lluka, L. J., & Chunduri, P. (2021). Redesigning a first year physiology course using learning analytics to improve student performance. *International Journal of Learning Analytics and Artificial Intelligence for Education*, *3*(1), 4-19.

Zheng, K., Yang, X., Wang, Y., Wu, Y., & Zheng, X. (2020). Collaborative filtering recommendation algorithm based on variational inference. *International Journal of Crowd Science*, *4*(1), 31-44.