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Exploring Algorithmic Approaches for Academic Interest Classification in Application: UMS Study Case

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Abstract. The COVID-19 pandemic has led to new learning models at universities, posing challenges for educators and students. This situation will likely have an impact on the mental health of most students due to the lack of face-to-face interaction when distance learning is implemented. While social distancing is critical to reducing new cases of COVID-19, implementing new learning models at universities presents significant challenges. This study aims to categorize student interests in discussion room applications by applying machine learning model. The machine learning models employed include Random Forest, Naive Bayes, XGBoost, CatBoost, and LightGBM. The procedure of this research consists of several steps, starting from data collection, data preprocessing, classification, model evaluation, model testing, and deployment. The result shows that Random Forest has performed the best in this classification task compared to other four models. The testing result of the system shows that the recommended academic interest tags are mostly relevant to user preferences, accounting for 71.24%. In addition, this finding offers insights into addressing the pandemic's impact on students and highlights technology's potential to improve the educational experience, emphasizing the need for increased mental health resources.

Keywords: online learning, covid-19, academic interest, machine learning

1. Introduction

During the critical phase of the COVID-19 pandemic, implementing social distancing was essential to reduce the number of new COVID-19 cases (Julie et al., 2022). This uncertainty has prompted heightened concerns, leading governments to implement stringent lockdown measures and enforce various social distancing regulations (Moll-Khosrawi et al., 2024). Consequently, the initial teaching models in many universities were implemented online, where students were isolated, and classes could not be taught face-to-face, exacerbating the challenges faced by both educators and learners (Rodríguez-Molinero et al., 2024). All the difficulties encountered by students in remote learning amid the COVID-19 pandemic possess significant potential to trigger mental health concerns among them (Izzatika et al., 2021).

Many individuals experience feelings of stress and being stretched too thin, concerns about exposing their family or network to illness, emotional and physical exhaustion, and a lack of adequate emotional support from colleagues (Montero-Marin et al., 2023). The educator could not evaluate the student this way during COVID-19, and the student could not observe the educator (De

Kock et al., 2022). Moreover, educators could not assess students in traditional ways, and students could not observe or interact with their educators as they usually would (Çağlar & Okuyan, 2024).

Previous research indicates that adolescents are susceptible to negative influences compounded by the COVID-19 crisis. Despite extensive efforts in online education, adolescents still find it tedious, possibly due to factors like learning environment and teaching style (Ohlmeier et al., 2022). Spending most of the time at home during quarantine resulted in an inability to socialize with friends, potentially leaving students bored and depressed (Chansaengsee, 2023). The prolonged isolation and lack of face-to-face interaction have impacted students academically, emotionally, and psychologically (Alomyan, 2021). With the usual avenues for socialization and support, many students have been able to cope with the challenges of remote learning and the pandemic (Al-Maskari et al., 2021). Additionally, educators' absence of direct feedback has left students feeling disconnected and uncertain about their academic progress (Aljedaani et al., 2023). As a result, there is a growing concern about the mental well-being of students, especially adolescents, who are particularly vulnerable during this crisis (Ho et al., 2023). Despite efforts to provide online education and support services, the overwhelming demand for assistance from university counselling services underscores the urgent need for more comprehensive mental health resources (Pandya & Lodha, 2022) and strategies to address the psychological toll of the pandemic on students (Cowie & Myers, 2020).

The current research focuses on assessing and categorizing student achievement and involvement in discussion room applications—a critical component of learning via the internet. Using the Universitas Muhammadiyah Surakarta (UMS) as a case study, this study investigates how well different machine learning algorithms identify students who are studying the same subject. By incorporating machine learning into educational technologies, teachers will be able to customize interventions and support mechanisms based on data-driven insights, thereby improving student results. (Ayanwale et al., 2024). There is a lot of interest in the application of machine learning in educational settings, and many research have looked into how it might improve learning outcomes and experiences (Ali et al., 2024). For instance, Scientists have utilized many algorithms, including random forest algorithms, decision trees, support vector machines, neural networks, and (Panagiotakopoulos et al., 2021), to forecast student performance, identify students who are at risk, and customize educational materials (Webb et al., 2021).

In this regard, the current study attempts to assess how well various machine learning algorithms identify students in the group discussion application within the same academic focus area. By evaluating these algorithms' accuracy, recall, precision, F1 score, and cross-validation (Chang et al., 2022).

The goal of this study is to determine which approach works best in this particular educational environment. In order to identify which classical categorization method offers the most trustworthy and useful insights, this study will compare them. (Lemay et al., 2021). This comparison examination is essential to comprehending each algorithm's advantages and disadvantages in a practical teaching setting. (Sarker, 2021).

The results of this study will add to the expanding corpus of information on the use of machine learning in education and offer useful advice to administrators and lecturers at UMS and elsewhere. These realizations can guide the creation of more efficient online learning environments and support networks, which will eventually improve students' educational experiences. (Haleem et al., 2022). The findings of this study may also have wider ramifications for the planning and execution of instructional technology, pointing to fresh avenues for investigation and advancement in this area.

This study, taken as a whole, shows how machine learning has the power to change online learning environments, boosting overall educational outcomes and making them more responsive to the requirements of individual students. The analysis highlights how important technology will be in determining how educational will develop in the years following the pandemic by solving the difficulties in engaging students and finding them academically compatible. (Li et al., 2023). Using advanced analytical tools in the classroom is expected to boost student achievement and provide more welcoming and encouraging learning environments. (Celik, 2023). The knowledge gathered from this research will be crucial in directing future developments and guaranteeing that every student has the chance of achievement as educational institutions continue to manage the challenges of learning via the internet. (Kamalov et al., 2023).

2. Method

This research was conducted using five machine learning classification algorithms, namely Random Forest, Naive Bayes, CatBoost, XGBoost, and LightGBM. The primary purpose of this study is to compare the performance of the five algorithms and choose the best model based on several evaluation metrics, namely recall, precision, accuracy, f1-score, and k-fold cross-validation.

In detail, the procedure of this research involves multiple consecutive phases, as depicted in Figure 1.

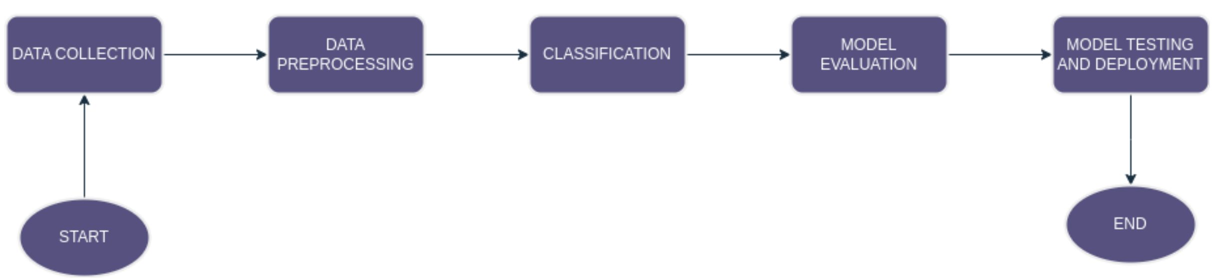


Figure 1. The Procedure of the Research

a. Data Collection

The dataset used in this study was obtained from surveys distributed via Google Forms to various academic programs at UMS in 2023. It covers a wide range of information, capturing details such as the academic programs pursued during high school and university, current levels of interest in academic programs, leisure activities, preferred reading themes, motivations for social media usage, and interests in various fields. In total, the dataset comprises 1,168 instances, each representing a unique respondent, and consists of 23 attributes, reflecting the different aspects of respondents' educational backgrounds, interests, and preferences, as described in Table 1.

Table 1. Attributes of the Dataset and Their Description

Code	Attribute	Description	Value
Q1	Program Studi di UMS (contoh: Teknik Kimia, awali huruf dengan kapital)	Study program while studying at UMS	Name of study program
Q2	Program Studi saat SMA/SMK/MA (Contoh: Teknik Kimia atau Mipa, awali huruf dengan kapital)	Study Program during High School	Name of study program
Q3	Seberapa besar minat Anda dalam program studi saat ini?	Assess enthusiasm for the current major	Linear scale (1-5), 1= not very interested, 5= very interested
Q4	Sebutkan sub-bidang spesifik dalam program studi Anda yang paling menarik bagi Anda? (awali huruf dengan kapital)	interest in specific aspects of the academic program	Name of spesific aspects of the academic program
Q5	Apa motivasi Anda bergabung ke sosial media seperti LinkedIn, Instagram, dan sosial media lain	reason to join social media such as LinkedIn, Instagram, and other social media	List of user Motivations
Q6	Apakah Anda tertarik untuk meneliti makhluk hidup?	Interest in researching living organisms.	Yes, No
Q7	Apakah Anda tertarik untuk menghitung dan mencatat data statistik dan numerik lainnya?	Interest in calculating and recording statistical and other numerical data.	Yes, No
Q8	Apakah Anda tertarik untuk melakukan pekerjaan sukarela di organisasi non-profit?	Interest in volunteering for non-profit organizations.	Yes, No
Q9	Apakah Anda tertarik dalam satu aspek seni tertentu?	Interest in a specific aspect of art.	Yes, No
Q10	Apakah Anda tertarik dalam mengembangkan perangkat lunak, keamanan komputer, jaringan, atau hal lain dalam dunia TIK?	Interest in software development, computer security, networking, or other aspects of the IT world.	Yes, No
Q11	Apakah Anda tertarik dalam ilmu engineering?	Interest in engineering science.	Yes, No
Q12	Apakah Anda tertarik pada aspek-aspek tertentu dalam bidang pendidikan?	Interest in specific aspects within the field of education.	Yes, No
Q13	Apakah Anda tertarik untuk mempelajari bahasa?	Interest in language learning.	Yes, No
Q14	Apakah Anda tertarik mengikuti	Interested in following	Yes, No

Code	Attribute	Description	Value
	perkembangan dalam bidang ekonomi?	developments in the field of economics.	
Q15	Apakah Anda tertarik dalam proyek bisnis yang ingin Anda jalankan di masa depan?	Interest in future business projects.	Yes, No
Q16	Apakah Anda tertarik dengan hal-hal yang terkait dengan kebudayaan?	Interest in cultural-related matters.	Yes, No
Q17	Apakah Anda tertarik dalam bidang hukum?	Interest in the field of law	Yes, No
Q18	Apakah Anda tertarik pada riset medis atau penelitian kesehatan lainnya?	Interest in medical research or other health-related studies.	Yes, No
Q19	Aktivitas waktu luang favorit Anda adalah ?	Favorite leisure activities.	List of user leisure activities
Q20	Tema bacaan apa yang Anda minati?	Preferred reading themes	Name of reading themes
Q21	Apa topik berita atau informasi yang paling sering menarik perhatian Anda? (Jika memilih lainnya wajib diisi dan awali huruf dengan kapital)	Most intriguing news topics or information	Name of news topics

b. Data Preprocessing

The data preprocessing stage in this research aims to ensure the quality and consistency of the data and that it is ready for in-depth analysis (Joshi et al., 2021). This phase includes cleaning the text, such as removing special characters, removing spaces and conjunctions, encoding certain features into numeric using several techniques, separating the text into tokens at the tokenization stage, and then reducing word variations to their primary form. This research is more inclined to lemmatization, for common words with no meaning can be handled with stopword removal. If the dataset has data integrity, then oversampling is commonly used.

c. Classification

In data science, classification methodologies hold significant importance in converting extensive and heterogeneous datasets into practical insights. With data continual expansion and intricacy, the demand for resilient and effective classification techniques has surged. This study investigates the utilization of different machine learning algorithms for classification within a designated field. The focus is directed towards the exploration of the five algorithms that are, Random Forest, Naive Bayes, XGBoost, CatBoost, and LightGBM.

Random Forest is an ensemble learning method for classification, regression, and other tasks that operates by building many decision trees at training time and outputting the class mode (classification) or average prediction (regression) from each tree (Kiangala & Wang, 2021). Naive Bayes is a probabilistic machine learning algorithm based on Bayes' theorem which performs well in many real-world situations, particularly in text classification and spam filtering (Sarker, 2021). XGBoost stands for extreme gradient boosting which effectively boosts and more accurate rather than a single decision tree algorithm (Kiangala & Wang, 2021). CatBoost is known for its ability to handle categorical features directly without requiring pre-processing and its support for GPU training (Tokmak et al., 2023), while LightGBM is designed for distributed and efficient training of large-scale datasets and is known for its speed and memory efficiency (Khan et al., 2023).

d. Model Evaluation

To evaluate the models applied in this study, four parameters were used. They are Recall, Precision, Accuracy, F1-Score, and K-fold Cross-Validation evaluation metrics.

Recall is the proportion of positive events correctly identified by the model (Dholpuria et al., 2018). The result of Recall can be calculated using Equation 1. *Precision* is used to measure positive patterns that are predicted correctly from the total predicted patterns in the positive class (Jordan & Mitchell, 2020), as described in Equation 2. *Accuracy* is a measure of overall model performance that measures the proportion of all correct predictions compared to the total number of predictions (Kulkarni et al., 2020), as described in Equation 3. *F1-Score* represents the harmonic mean between recall and precision values (Priyambudi & Nugroho, 2024), as counted using Equation 4 (Jordan & Mitchell, 2020). *K-fold cross-validation* divides the data into k roughly equal parts, called "folds." This results in k different pairs of training and testing sets, where each pair is created by excluding one-fold from the entire dataset to serve as the test set (Yates et al., 2023). The estimated score for a single k-fold cross-validation is calculated using Equation 5.

$$Recall = Tp/(Tp+Fn) \quad \text{(1)}$$
$$Precision = Tp/Tp+Fp \quad \text{(2)}$$
$$Accuracy = TN+TP/TN+FP+FN+TP \quad \text{(3)}$$

Where:

Tp = Amount of True Positive
Tn = Amount of True Negative
Fp = Amount of False Positive
Fn = Amount of False Negative

$$F1\ Score = 2*p*r/p+r \quad \text{(4)}$$
$$Estimated\ score = \frac{1}{k}\sum_{i=1}^{k} Score_i \quad \text{(5)}$$

Where:

p : precision, the ratio of correctly predicted positive observations to total optimistic predictions.

r : recall, the ratio of correctly predicted positive observations to all compliances in the actual class

k : the average is calculated based on the total score obtained.

i : individual scores from 1 to k are taken as the average

e. Model Testing and Deployment

In this phase, the best model is identified by utilizing MLflow to manage the machine learning lifecycle. MLflow provides tools and features that make it easy for data scientists and engineers to track experiments, deploy models, and manage models in production (Kreuzberger et al., 2023, Nicklin et al, 2022). To find the best model, five classification algorithms are evaluated in terms of Accuracy, Recall, Precision, F1 Score, and k-fold cross-validation. The dataset was divided into 80% for training and 20% for testing.

Based on the evaluation metrics shown in Table 2, the accuracy of various algorithms ranges from 53.98% to 71.51%. It is known that Random Forest performs the best in all metrics compared to other five algorithms, with 71.51% in both Recall and Accuracy, 75.90%, 73.12%, and 70% in Precision, F1 Score, and k-fold cross validation, respectively. Since Random Forest shows the best model in this case, thus, this model is then deployed to the system.

Table 2. Comparison Results of the Evaluation Metrics Across Five Algorithms

Model	Recall	Precision	Accuracy	F1 Score	k-fold cross validation
Random forest	71.51%	75.90%	71.51%	73.12%	70%
Naïve Bayes	56.57%	62.59%	56.57%	56.26%	56%
XGBoost	62.35%	66.59%	62.35%	64.01%	60%
CatBoost	53.98%	55.32%	53.98%	53.93%	53%
LightGBM	63.94%	65.62%	63.94%	64.60%	59%

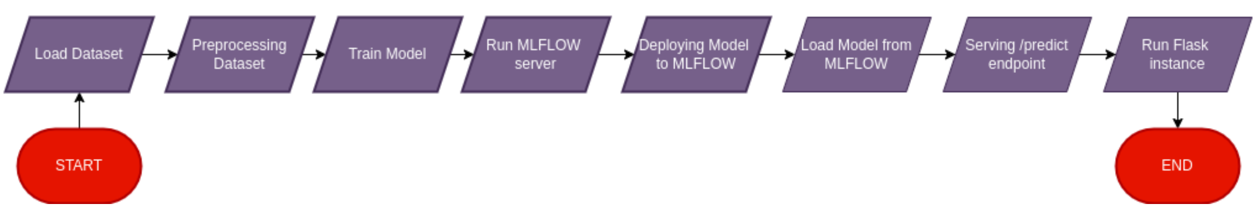


Figure 2. Training and deployment of the Random Forest model using MLflow and Flask

Figure 2 describes the deployment of the Random Forest model in the system using MLflow. Model deployment with MLflow simplifies the process of serving machine learning models for real-time predictions without requiring complicated server settings. Other applications can access and use Deployed models via a REST API, allowing easy integration into various applications. This workflow starts from receiving data at the prediction endpoint, preprocessing the data, sending the data to the model deployed on the MLflow server, and returning the prediction results to the application.

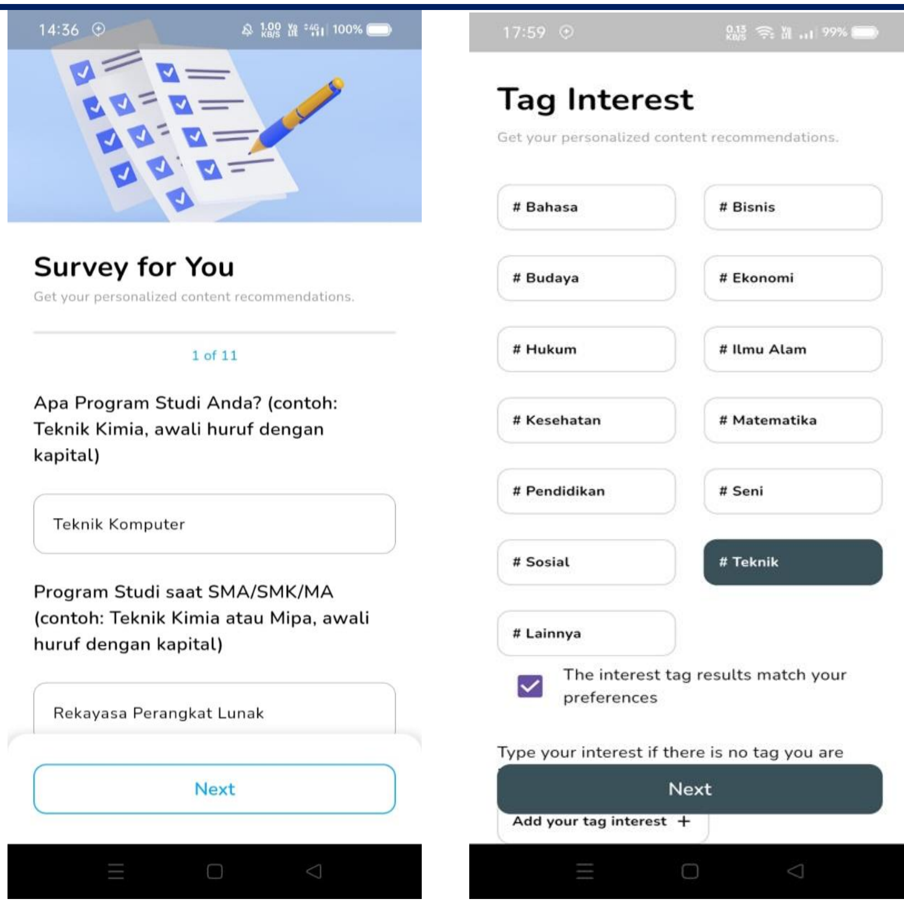
3. Result and Discussion

a. System Deployment and Testing

Random Forest model has emerged as a robust and widely-used machine learning technique for various applications, including system deployments aimed at enhancing user experiences through personalized recommendations. Its effectiveness lies in its ability to handle large datasets with numerous features while maintaining high predictive accuracy. In the context of the system being discussed, the Random Forest model has been implemented successfully, marking a significant milestone in leveraging machine learning to improve user interactions.

Figure 3(a) showcases the survey page within the system, designed to capture users' academic interests effectively. This page serves as a pivotal component, allowing users to input their preferences, which are then utilized by the Random Forest model to generate personalized tags. These tags play a crucial role in tailoring the user experience, ensuring that the system delivers content and recommendations that align closely with individual interests. Meanwhile, Figure 3(b) illustrates the application interface dedicated to the personalized interest tag recommendation feature. This interface serves as a user-friendly platform where users can view and adjust the tags recommended by the system based on the output of the Random Forest model. This iterative process ensures that the recommendations evolve with user interactions, becoming increasingly accurate and aligned with changing preferences over time (Hamutoglu et al, 2020).

By integrating the Random Forest model into the system architecture, stakeholders benefit from enhanced decision-making capabilities driven by machine learning. The model's ability to handle complex data relationships and deliver reliable predictions contributes to a more intuitive and responsive user experience. Moreover, its deployment underscores the commitment to leveraging advanced technologies to meet user needs effectively in today's dynamic digital landscape. In summary, the successful deployment of the Random Forest model in the system represents a significant advancement in utilizing machine learning for personalized user interactions. Figures 3(a) and 3(b) provide visual insights into how the model facilitates the collection of user preferences and subsequently refines recommendations, thereby enhancing the overall usability and effectiveness of the system. This approach not only improves user satisfaction but also underscores the system's adaptability and scalability in accommodating diverse user preferences and evolving requirements.



(a) Page of Survey (b) Page of Interests Tag Recommendation

Figure 3. UpMate System for recommending interests tag for academicians

The application depicted in Figure 3 represents a significant advancement in leveraging technology to enhance user connectivity based on shared academic interests. Developed with the intention of fostering meaningful connections among users, the application underwent rigorous manual testing to validate its functionality and performance across various parameters. These parameters included testing within different application environments, inputting diverse datasets, and meticulously verifying the outputs generated by the underlying model (Nachouki et al, 2023).

Table 3 outlines the specific test instruments employed during these validation procedures, emphasizing the thoroughness with which the application's capabilities were scrutinized. The primary objective throughout testing was to ensure that the model, having undergone rigorous training and evaluation phases, could effectively adapt to and accommodate the diverse preferences and interactions expected in a live production environment.

Table 3. Two examples of Manual Testing Scenario of the System Using Test Instrument

No	Environment	Input (Question and Possible Answer)	Output	Status
1	Generating interests tag in low-speed internet connection (<= 5 mbps)	Q1: Gizi; Q2: Ilmu Pengetahuan Alam; Q3: 2; Q4: Teknologi Informasi; Q5: Networking; Q6: Tidak; Q7: Tidak; Q8: Tidak; Q9: Ya; Q10: Tidak; Q11: Ya; Q12: Tidak; Q13: Ya; Q14: Tidak; Q15: Tidak; Q16: Ya; Q17: Tidak; Q18: Ya; Q19: Menonton Film; Q20: Seni; Q21: Politik	Interest Tag: Bahasa	Irrelevant
2	Generating interests tag in low-speed internet connection (<= 5 mbps)	Q1: Informatika; Q2: Multimedia; Q3: 4; Q4: Pemrograman; Q5: Inovasi; Q6: Ya; Q7: Tidak; Q8: Ya; Q9: Ya; Q10: Ya; Q11: Ya; Q12: Ya; Q13: Tidak; Q14: Ya; Q15: Tidak; Q16: Ya; Q17: Ya; Q18: Tidak; Q19: Menulis; Q20: Non-fiksi; Q21: Teknologi	Interest Tag: TIK	Relevant

Table 3 provides a comprehensive overview of the system's functionality in analyzing and categorizing input queries to generate meaningful interest tags. These tags play a pivotal role in connecting users who share similar academic interests within the system. By classifying input queries and mapping them to relevant tags, the system facilitates enhanced user interactions and engagement, fostering a community where users can connect based on their academic pursuits.

Table 3 highlights the system's dynamic adaptability. It showcases how the system adjusts its output based on two critical factors: user feedback and performance evaluation. User feedback serves as a crucial mechanism for refining the relevance and accuracy of interest tag recommendations. This iterative process ensures that the system continuously evolves to meet user expectations and preferences effectively.

In addition to generating interest tags and adapting based on user feedback, the system's performance is rigorously evaluated through output relevance measurements. The relevance assessment gauges the extent to which the interest tags generated align with users' expectations. Tags that closely match user expectations are classified as relevant, indicating a high degree of accuracy and utility. Conversely, tags that deviate significantly from user expectations are deemed irrelevant, prompting further refinement and improvement efforts.

By incorporating these evaluation metrics, the system not only enhances user satisfaction but also underscores its commitment to delivering precise and personalized recommendations. This approach ensures that the system remains responsive to evolving user needs and preferences, thereby fostering a robust and engaging platform for academic collaboration and interaction. Table 3 thus serves as a testament to the system's capability to analyze, adapt, and deliver relevant outputs that enrich the user experience within the academic community.

Table 4. Number of Relevancy Between the Input Data and User Expectation

Status	Quantity	Percentage
Relevant	166	71.24%
Irrelevant	67	28.76%
Total	**233**	**100.00%**

As detailed in Table 4, during testing, 233 input data points were processed by the system, revealing that 71.24% of these inputs aligned with user preferences, which demonstrates a significant achievement aligned with the study's objectives. This indicates that the system effectively identifies and recommends academic interest tags that resonate with users, thereby enhancing their engagement and satisfaction within the platform. the data also highlights an opportunity for refinement, as 28.76% of the generated tags were deemed irrelevant to user preferences. This discrepancy underscores the need for ongoing improvements to the system's algorithms and processes. Enhancements could focus on better distinguishing nuanced user preferences, reducing instances where inappropriate or less relevant tags are generated.

Addressing this area for improvement could involve fine-tuning the model's parameters, enhancing the algorithm's sensitivity to subtle variations in user input, and leveraging more sophisticated techniques for evaluating and validating tag relevance. By refining these aspects, the system can potentially reduce the percentage of irrelevant tags, thereby further enhancing its utility and user satisfaction. Overall, while the system has demonstrated commendable performance in aligning a significant majority of tags with user preferences, acknowledging and addressing the remaining 28.76% is essential for achieving optimal functionality. This iterative approach to enhancement ensures that the system evolves to meet the evolving needs and expectations of its users, reinforcing its role as a valuable tool for facilitating meaningful academic connections and interactions.

4. Conclusion

This research explores the potential of various machine learning algorithms to improve educational technology, particularly in discussion room applications. In this paper, Random Forest performs the best in all evaluation metrics compared to Naive Bayes, XGBoost, CatBoost, and LightGBM. Due to its performance, this model was chosen to be implemented into the system for interest tags recommendation process. The result of the system manual testing shows that 71.24% interest tags are relevant to users preferences. It indicates the succesfulness of the system development to recommend the interest tags for users. For future work, the application presents the applicative potential in increasing the functionality to be implemented in the educational sector and improving the overall user experiences.

5. References

Al-Maskari, A., Al-Riyami, T., & Kunjumuhammed, S. K. (2022). Students academic and social concerns during COVID-19 pandemic. *Education and information technologies*, *27*(1), 1-21. https://doi.org/10.1007/s10639-021-10592-2

Ali, O., Murray, P. A., Momin, M., Dwivedi, Y. K., & Malik, T. (2024). The effects of artificial intelligence applications in educational settings: Challenges and strategies. *Technological Forecasting and Social Change*, *199*, 123076. https://doi.org/10.1016/j.techfore.2023.123076

Aljedaani, W., Krasniqi, R., Aljedaani, S., Mkaouer, M. W., Ludi, S., & Al-Raddah, K. (2023). If online learning works for you, what about deaf students? Emerging challenges of online learning for deaf and hearing-impaired students during COVID-19: a literature review. *Universal access in the information society*, *22*(3), 1027-1046. https://doi.org/10.1007/s10209-022-00897-5

Alomyan, H. (2021). The Impact of Distance Learning on the Psychology and Learning of University Students during the Covid-19 Pandemic. *International Journal of Instruction*, *14*(4), 585–606. https://doi.org/10.29333/iji.2021.14434a

Ayanwale, M. A., Molefi, R. R., & Oyeniran, S. (2024). Analyzing the evolution of machine learning integration in educational research: a bibliometric perspective. *Discover Education*, *3*(1), 47. https://doi.org/10.1007/s44217-024-00119-5

Çağlar, S., & Okuyan, C. B. (2024). The impact of distance learning on the attitudes of nursing students: An online survey study. *Acta Scientiarum. Health Sciences*, *46*(1). https://doi.org/10.4025/actascihealthsci.v46i1.63213

Celik, I. (2023). Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. *Computers in Human Behavior*, *138*, 107468. https://doi.org/10.1016/j.chb.2022.107468

Chang, V., Ganatra, M. A., Hall, K., Golightly, L., & Xu, Q. A. (2022). An assessment of machine learning models and algorithms for early prediction and diagnosis of diabetes using health indicators. *Healthcare Analytics*, *2*, 100118. https://doi.org/10.1016/j.health.2022.100118

Chansaengsee, S. (2023). Boredom in online activity during COVID-19 outbreak causing dysfunctional behaviors of adolescent students: phenomenological study to the creation of virtual reality classroom. *European Journal of Psychology of Education*, *02562928*(02562928). https://doi.org/10.1007/s10212-022-00673-2

Cowie, H., & Myers, C. (2020). The Impact of the COVID-19 Pandemic on the Mental Health and Well-being of Children and Young People. *Children & Society*, *35*(1), 62–74. https://doi.org/10.1111/chso.12430

De Kock, J. H., Latham, H. A., & Cowden, R. G. (2022). The mental health of healthcare workers during the COVID-19 pandemic: a narrative review. *Current Opinion in Psychiatry*, *35*(5), 311-316. https://doi.org/10.1097/yco.0000000000000805

Dholpuria, T., Rana, Y. K., & Agrawal, C. (2018). A sentiment analysis approach through deep learning for a movie review. In *2018 8th International Conference on Communication Systems and Network Technologies (CSNT)* (pp. 173-181). IEEE. https://doi.org/10.1109/CSNT.2018.8820260

Haleem, A., Javaid, M., Qadri, M. A., & Suman, R. (2022). Understanding the role of digital technologies in education: A review. *Sustainable Operations and Computers*, *3*(3), 275–285. https://doi.org/10.1016/j.susoc.2022.05.004

Hamutoglu, N. B., Gemikonakli, O., Duman, I., Kirksekiz, A., & Kiyici, M. (2020). Evaluating students experiences using a virtual learning environment: satisfaction and preferences. *Educational Technology Research and Development*, *68*(1), 437-462. https://doi.org/10.1007/s11423-019-09705-z

Ho, D. G., Sa'adi, M., He, D., & Hoon, C. Y. (2023). Silence over the wire: student verbal participation and the virtual classroom in the digital era. *Asia Pacific Education Review*, *24*(4), 599-615. https://doi.org/10.1007/s12564-023-09834-4

Izzatika, M., Syakurah, R.A., & Bonita, I. (2021). Indonesia's mental health status during the Covid-19 pandemic. Indigenous: Jurnal Ilmiah Psikologi, 6(2). 78-92. doi: http://dx.doi.org/10.23917/indigenous.v6i2.11945

Jordan, M. I., & Mitchell, T. M. (2020). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255–260. https://doi.org/10.1126/science.aaa8415

Joshi, A. P., & Patel, B. V. (2021). Data preprocessing: The techniques for preparing clean and quality data for data analytics process. *Oriental Journal of Computer Science and Technology*, 13(2-3), 78–81. https://doi.org/10.13005/OJCST13.0203.03

Julie, H., Rianasari, V. F., & Apriani, M. S. (2022). Indonesian mathematics teachers' views on distance learning barriers during the early Covid-19 pandemic. JRAMathEdu (Journal of Research and Advances in Mathematics Education), 7(1), 27–35. https://doi.org/10.23917/jramathedu.v7i1.15616

Kamalov, F., Calonge, D. S., & Gurrib, I. (2023). New Era of Artificial Intelligence in Education: Towards a Sustainable Multifaceted Revolution. Sustainability, 15(16), 12451. https://doi.org/10.3390/su151612451

Khan, A. A., Chaudhari, O., & Chandra, R. (2023). A Review of Ensemble Learning and Data Augmentation Models for Class Imbalanced problems: Combination, Implementation and Evaluation. *Expert Systems with Applications*, *244*, 122778. https://doi.org/10.1016/j.eswa.2023.122778

Kiangala, S. K., & Wang, Z. (2021). An effective adaptive customization framework for small manufacturing plants using extreme gradient boosting-XGBoost and random forest ensemble learning algorithms in an Industry 4.0 environment. *Machine Learning with Applications*, *4*, 100024. https://doi.org/10.1016/j.mlwa.2021.100024

Kreuzberger, D., Kühl, N., & Hirschl, S. (2023). Machine learning operations (mlops): Overview, definition, and architecture. *IEEE access*, *11*, 31866-31879. https://doi.org/10.1109/access.2023.3262138

Kulkarni, A., Chong, D., & Batarseh, F. A. (2020). Foundations of data imbalance and solutions for a data democracy. *Data Democracy*, 83–106. https://doi.org/10.1016/b978-0-12-818366-3.00005-8

Lemay, D. J., Baek, C., & Doleck, T. (2021). Comparison of learning analytics and educational data mining: A topic modeling approach. *Computers and Education: Artificial Intelligence*, *2*, 100016. https://doi.org/10.1016/j.caeai.2021.100016

Li, L., Zhang, R., & Piper, A. M. (2023). Predictors of student engagement and perceived learning in emergency online education amidst COVID-19: A community of inquiry perspective. *Computers in Human Behavior Reports*, *12*, 100326. https://doi.org/10.1016/j.chbr.2023.100326

Moll-Khosrawi, P., Küllmei, J., Chindris, V., Ganzhorn, A., Haus, J. M., Zöllner, C., & Schulte-Uentrop, L. (2024). Medical student´ s motivational changes during the COVID-19 university lockdown: a mixed-method study. *BMC Medical Education*, *24*(1), 226. https://doi.org/10.1186/s12909-024-05204-9

Montero-Marin, J., Hinze, V., Mansfield, K., Slaghekke, Y., Blakemore, S. J., Byford, S., Dalgleish, T., Greenberg, M. T., Viner, R. M., Ukoumunne, O. C. and Ford, T. (2023). Young People's Mental Health Changes, Risk, and Resilience During the COVID-19 Pandemic. *JAMA Network Open*, *6*(9), e2335016. https://doi.org/10.1001/jamanetworkopen.2023.35016

Nachouki, M., Mohamed, E. A., Mehdi, R., & Abou Naaj, M. (2023). Student course grade prediction using the random forest algorithm: Analysis of predictors' importance. *Trends in Neuroscience and Education*, 100214. https://doi.org/10.1016/j.tine.2023.100214

Nicklin, L. L., Wilsdon, L., Chadwick, D., Rhoden, L., Ormerod, D., Allen, D., Witton, G., & Lloyd, J. (2022). Accelerated HE digitalisation: Exploring staff and student experiences of the COVID-19 rapid online-learning transfer. *Education and Information Technologies*, *27*(6), 7653-7678. https://doi.org/10.1007/s10639-022-10899-8

Ohlmeier, S., Klingler, C., Schellartz, I., & Pfaff, H. (2022). Having a Break or Being Imprisoned: Influence of Subjective Interpretations of Quarantine and Isolation on Boredom. *International Journal of Environmental Research and Public Health*, *19*(4), 2207. https://doi.org/10.3390/ijerph19042207

Panagiotakopoulos, T., Kotsiantis, S., Kostopoulos, G., Iatrellis, O., & Kameas, A. (2021). Early dropout prediction in MOOCs through supervised learning and hyperparameter optimization. *Electronics*, *10*(14), 1701. https://doi.org/10.3390/electronics10141701

Pandya, A., & Lodha, P. (2022). Mental health consequences of COVID-19 pandemic among college students and coping approaches adapted by higher education institutions: A scoping review. *SSM-Mental Health*, *2*, 100122. https://doi.org/10.1016/j.ssmmh.2022.100122

Priyambudi, Z. S., & Nugroho, Y. S. (2024). Which algorithm is better? An implementation of normalization to predict student performance. In *AIP Conference Proceedings* (Vol. 2926, No. 1). AIP Publishing. https://doi.org/10.1063/5.0182879

Rodríguez-Molinero, J., Corral-Liria, I., Jiménez-Fernández, R., Ramírez-Puerta, R., González-Martín, S., Delgado-Somolinos, E., Losa-Iglesias, M. E., & López-Sánchez, A. F. (2024). Resilience and psychological factors among dentistry students who received face-to-face lectures during the COVID-19 pandemic. *BMC Medical Education*, *24*(1), 446. https://doi.org/10.1186/s12909-024-05445-8

Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Computer Science*, *2*(3), 1–21. Springer. https://doi.org/10.1007/s42979-021-00592-x

Tokmak, A. V., Akbulut, A., & Catal, C. (2023). Boosting the visibility of services in microservice architecture. *Cluster Computing*, 1-13. https://doi.org/10.1007/s10586-023-04132-5

Webb, M. E., Fluck, A., Magenheim, J., Malyn-Smith, J., Waters, J., Deschênes, M., & Zagami, J. (2021). Machine learning for human learners: opportunities, issues, tensions and threats. *Educational Technology Research and Development*, *69*(4), 2109-2130. https://doi.org/10.1007/s11423-020-09858-2

Yates, L. A., Aandahl, Z., Richards, S. A., & Brook, B. W. (2023). Cross validation for model selection: a review with examples from ecology. *Ecological Monographs*, *93*(1), e1557. https://doi.org/10.1002/ecm.1557