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AI-Driven Academic Achievement Tracker

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Abstract
Currently, colleges and universities manage certificates for students and faculty in physical formats, which is inefficient and cumbersome. In addition, tracking class advisor records, faculty participation certificates, YouTube lectures, and student placement details is a challenging process that complicates the generation of academic reports for each department. This manual technique interferes with the capacity to keep correct records, reducing institutional efficiency and production. This paper aims to overcome these issues by creating a centralized system for automating the collecting and maintenance of certificates and related academic data. By digitizing certificates and adding data such as event attendance, placement records, and faculty-led events, the system improves administration and reporting efficiency. This paper improves institutional operations by implementing a recommendation system that proposes skill-based courses and project ideas to students based on their academic and extracurricular activities, allowing them to expand their knowledge and abilities. With these improvements, the system optimizes institutional procedures, minimizes manual effort, and enhances overall academic management.
Keywords: *Academic Report Generator, Course and Project Recommendation, Certificate Collection, Hybrid Filtering*

1. Introduction
In today's academic and professional environments, managing certificates and tracking skill development are critical tasks for both students and faculty. Traditionally, institutions have relied on manual or paper-based systems to collect and maintain certificates from events such as workshops, seminars, and co-curricular activities. However, such approaches are inefficient, error-prone, and lack scalability, leading to significant administrative overhead and challenges in tracking individual progress. The need for an automated system that streamlines certificate management, tracks academic progress, and recommends future learning opportunities has become increasingly apparent [1]. This paper addresses these inefficiencies by developing a Certificate Management System that leverages Artificial Intelligence (AI) and Machine Learning (ML) to provide intelligent, role-based recommendations for students, faculty, and administrators. The proposed system not only automates the collection and management of certificates but also provides personalized recommendations for courses and projects based on students' past achievements and current skills. By utilizing content-based filtering, the system compares user profiles (certificates and skills) with available learning opportunities, while collaborative filtering identifies patterns among similar users to suggest relevant courses and projects [2]. Additionally, features such as Natural Language Processing (NLP) for skill extraction, role-based recommendations, and LinkedIn API integration enhance the system's capability to track and manage skills and achievements in a more dynamic and efficient manner [3][4]. Moreover, this system incorporates a decision tree classifier for predicting student placement outcomes based on their academic and extracurricular data, employing reinforcement learning to continuously refine recommendations [5]. With the ability to adapt recommendations to different user roles (students, faculty, admin, super admin), the system ensures that all stakeholders in an academic institution can manage their records effectively while promoting

student growth through intelligent course and project suggestions [6]. this paper aims to revolutionize the certificate management process by combining automation with AI-driven insights, improving both efficiency and decision-making [7].

2. Literature Review

Personalized learning systems, leveraging Artificial Intelligence (AI) and Machine Learning (ML) algorithms, have gained significant traction in education. These systems aim to recommend courses, projects, and resources based on a student's academic history and interests. However, many existing models focus on either content-based or collaborative filtering methods in isolation, limiting the scope of accurate and personalized recommendations. Recent research advocates for hybrid filtering algorithms, which combine the strengths of both approaches to enhance accuracy and user satisfaction. This review explores the advancements in hybrid recommendation systems, focusing on their application to course and project recommendations based on skill extraction from certificates. Furthermore, the system's ability to generate detailed academic reports for institutions addresses an emerging need for automated and data-driven decision-making.

2.1 Skill-Based Course Recommendation System

V. Sankhe et al. [1] proposed a skill-based course recommendation system that utilizes a hybrid approach to suggest relevant courses to students. Their system combines fuzzy clustering to group students based on similar skills and course histories, helping to recommend courses that align with the students' abilities and career aspirations. This approach helps mitigate the cold-start problem, commonly encountered in recommendation systems. However, while fuzzy clustering offers flexibility in handling diverse student profiles, it can be computationally expensive when applied to large datasets, impacting real-time performance in large educational systems .

2.2 Learning Style-Based Ontology Matching for Learning Resources Recommendation

O. E. Aissaoui and L. Oughdhir [2] developed a learning style-based ontology matching approach to enhance the recommendation of learning resources. Their system integrates the Felder-Silverman Learning Style Model (FSLSM) to match students' learning preferences with corresponding resources. This approach improves engagement and knowledge retention by personalizing the learning experience. However, maintaining the ontology and ensuring its relevance in dynamic educational environments is a challenge, requiring continuous updates and adjustments to keep up with new learning materials .

2.3 Content-Based Recommendation Using Machine Learning

Y. Tai et al. [3] explored the use of machine learning algorithms in content-based recommendation systems. The study employed algorithms such as Logistic Regression, SVM, and CNN-LSTM to predict user preferences based on user-item interactions. While the system showed high accuracy in providing personalized recommendations, it was primarily focused on text-based content, limiting its application in multimedia-rich educational contexts. The use of neural networks, however, presents opportunities for expanding the system to handle more complex data types like video-based learning .

2.4 Survey on Recommendation System Methods

P. Nagarnaik and A. Thomas [4] conducted a survey on various recommendation system techniques, including content-based filtering, collaborative filtering, and hybrid methods. The paper highlighted the strengths and weaknesses of each approach, emphasizing the growing importance of hybrid systems in improving recommendation accuracy. Their findings suggest that while content-based systems offer more control over feature extraction, collaborative filtering models can provide more personalized recommendations by learning from user behavior. The survey further noted the cold-start and scalability issues inherent in both models, which hybrid approaches aim to mitigate.

2.5 Skill Detection from Resumes Using Natural Language Processing (NLP)

E. S. Chifu et al. [5] introduced a system for detecting professional skills from resumes using Natural Language Processing (NLP). This method can be applied to educational systems where certificates and academic achievements need to be

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analyzed to extract key skills. The proposed model utilized TF-IDF and Word Embeddings to process unstructured text and identify skills relevant to specific job or course recommendations. The system proved effective in automating the skill-matching process but required continuous tuning of the NLP models to maintain high accuracy across diverse certificate formats .

2.6 Collaborative Recommendation for Online Courses

R. Obeidat et al. [6] developed a collaborative recommendation system for online course suggestions. By clustering users with similar interests and course completion histories, the system recommended courses that other users in the same group had completed. While effective in improving recommendation accuracy, the system was limited by the cold-start problem for new users. Collaborative filtering systems like this often require large datasets to function efficiently, and for small educational institutions or systems with sparse data, the system's performance may be compromised.

2.7 Student Placement Analyzer Using Machine Learning

S. K. Thangavel et al. [7] developed a recommendation system focused on analyzing and predicting student placements using machine learning algorithms. The system applies classifiers such as Decision Trees and Random Forests to predict job placements based on academic achievements, skills, and extracurricular activities. The paper emphasizes the importance of considering both academic performance and non-academic activities when making placement recommendations. However, the study notes the limitations in predicting placement outcomes for students with unconventional career paths, as the system primarily relies on historical data.

2.8 Role-Based Contextual Recommendation

C. Zeng et al. [8] introduced a role-based recommendation system that provides contextual recommendations based on the user's role within an organization (student, faculty, or admin). The system adjusts its recommendations based on the user's activities and responsibilities, offering courses, projects, and professional development resources that align with their role. The paper highlights the benefits of contextual recommendations, particularly in academic institutions where different user groups have distinct needs. However, role-based systems can struggle with scalability as the number of roles and associated recommendations grows .

2.9 Collaborative Filtering for Recommender Systems

R. Zhang et al. [9] presented a study on collaborative filtering techniques for recommender systems. Their work focused on improving traditional collaborative filtering methods through matrix factorization techniques such as Singular Value Decomposition (SVD) and Alternating Least Squares (ALS). These methods were shown to enhance recommendation accuracy in educational systems by factoring in both user-item interactions and latent features. The main drawback of collaborative filtering, as discussed in the paper, remains its poor handling of sparse data and cold-start scenarios.

2.10 Artificial Intelligence-Based Recommendation System

P. Verma and S. Sharma [10] proposed an AI-based recommendation system that integrates both content-based and collaborative filtering methods. The system utilizes machine learning models to improve the precision of its recommendations, learning from both the user's preferences and their interactions with the system. The paper suggests that the combination of AI and ML algorithms can provide a more tailored and engaging user experience, especially in educational environments where personalized learning paths are crucial. However, the complexity of implementing such systems requires significant computational resources, which may be a barrier for smaller institutions.

2.11 Skill-Based Group Allocation for Project-Based Learning

R. Nand et al. [11] developed a skill-based group allocation system using Genetic Algorithms (GA). The system groups students for project-based learning courses by analyzing their skills and academic backgrounds. By considering multiple constraints such as skill diversity and project requirements, the system ensures balanced and

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efficient group formation. The use of genetic algorithms allows for a flexible and adaptive approach, but the computational complexity of GA can be challenging when dealing with large datasets or numerous constraints .

2.12 Personalized Learning Path Generation Using Reinforcement Learning

S. Sarkar and M. Huber [12] explored the use of Reinforcement Learning (RL) and Generative Adversarial Networks (GANs) to generate personalized learning paths for students in e-learning systems. By learning from student interactions and feedback, the system adapts its recommendations over time, ensuring that the learning path remains relevant and aligned with the student's goals. The use of RL allows for continuous improvement of the system, but its implementation in real-time educational systems can be computationally demanding.

2.13 OCR Assisted Translator

Nikhil Chigali, Sai Rohith Bobba, Suvarna Vani K., and Rajeswari S. [13] presented an OCR-Assisted Translator aimed at addressing India's multilingual challenges by enabling translation between English and native languages through image-based text extraction. The application combines Tesseract OCR and translator APIs like Google Translate to extract and translate text from documents or images. Implemented using Flutter, the system offers a user-friendly interface with features like language selection, block-based text translation, and flexible image input methods. The authors tested their solution on various scenarios, showcasing promising results and setting a foundation for future enhancements such as additional language support and document translations.

2.14 Role-Based Access Control in Software Services

M. Lasoň and O. Jakl [14] explored the theory and practice of Role-Based Access Control (RBAC) in software systems. Their paper highlights the importance of implementing role-based access in educational systems to ensure that different users (students, faculty, and admins) have appropriate access to information and system features. The study emphasizes that RBAC systems are essential for maintaining security and ensuring that recommendations are role-appropriate, but also warns of the scalability issues that can arise when managing large numbers of users and roles.

2.15 Optical Character Recognition using Tesseract and Classification

Saurabh Dome and Asha P. Sathe[15] explores the development of a web application leveraging OCR technology. This tool uses Tesseract for text recognition and a deep learning model for handwritten text classification, aiming to automate information extraction and reduce manual data entry costs. The study emphasizes enhancing accuracy, user experience, and cost-effectiveness, integrating real-time OCR capabilities, and handwritten text recognition. Their work highlights the potential for OCR to streamline workflows across diverse applications, with future plans for improved UI.

3. Discussion

The evolution of recommendation systems in educational contexts has demonstrated both the potential and limitations of various methodologies. A comprehensive literature review reveals that while substantial progress has been made in leveraging AI and ML for personalized learning, significant challenges remain. The studies highlighted offer insights into traditional content-based and collaborative filtering approaches, but they also underscore common pitfalls, such as the cold-start problem, the rigidity of static ontologies, and the computational complexity of fuzzy clustering. By examining these issues, we can identify how a hybrid filtering approach, combined with role-based access control, can enhance the effectiveness of course and project recommendations while also facilitating better management of academic records. A critical issue identified in the literature is the inefficiency of standalone recommendation systems. For instance, while Sankhe et al. [1] demonstrated the effectiveness of fuzzy clustering for personalized course recommendations, the model faced challenges in scalability and computational demands, especially in larger datasets. Similarly, Aissaoui and Oughdir [2] pointed out the difficulty of maintaining updated ontologies in ontology-based systems, which can hinder the accuracy of course recommendations when new skills or courses emerge

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4. Comparative Study

The Table 1 below show the comparative study of the AI driven Academic Achievement Tracker.

Table 1 Comparitive Study

REF. NO.	Author Name	Publication Year And Publisher	Title Of Paper	Methodology	Disadvantage
1	Viddhesh Sankhe, Janice Shah, Tejas Paranjape and Radha Shankarmani	2020 IEEE	Skill Based Course Recommendation System	Fuzzy c-means clustering for grouping students	Computationally complex. Recommendations can be ambiguous if interests are unclear.
2	Ouafae EL AISSAOUI and Lahcen OUGHDIR	2020 IEEE	A learning style-based Ontology Matching to enhance learning resources recommendation	Machine learning to match learning styles with ontologies	High implementation complexity. Performance relies on quality of training data.
3	Yifan Tai, Zhenyu Sun and Zixuan Yao	2021 IEEE	Content-Based Recommendation Using Machine Learning	Logistic regression, SVM, CNN-LSTM for predictions	Limited to text data. Misses potential from more complex multimedia data.
4	Paritosh Nagarnaik, A. Thomas	2015 IEEE	Survey on recommendation system methods	K-means clustering and CHARM for pattern discovery	Data preprocessing is time-consuming. Performance depends on K selection for clustering.
5	Emil St. Chifu, Viorica Rozina Chifu, Iulia Popa and Ioan Salomie	2017 IEEE	A system for detecting professional skills from resumes written in natural language	Ontology-based skill detection with part-of-speech patterns	Limited to predefined ontology scope. May misidentify non-skill phrases.
6	Raghad Obeidat, Rehab Duwairi and Ahmad Al-Aiad	2019 IEEE	A Collaborative Recommendation System for Online Courses Recommendations	K-means clustering and Apriori algorithm for course patterns	High computational complexity. Limited by reliance on historical data.
7	Sentkil Kumar Thangavel, P. Divya Bkaratki and Abijitk Sankar	2017 IEEE	Student placement analyzer: A recommendation system using machine learning	Decision tree classifier for placement prediction	Overfitting risk with insufficient data. Dependent on historical data quality.
8	Cheng Zeng; Liang Hong; Jian Wang; Chuan He; Jilei Tian; Xiaogang Yang	2011 IEEE	Role-Based Contextual Recommendation	Behavior analysis with contextual factors	Complex role mining process. Real-time updating challenges due to role changes.
9	Ruisheng Zhang, Qi-	2014 IEEE	Collaborative Filtering for Recommender	Matrix factorization for user-item	Struggles with sparse data.

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	dong Liu, Chun-Gui, Jia-Xuan Wei and Huiyi-Ma		Systems	preference prediction	Can be computationally intensive.
10	Priyash Verma and Shilpi Sharma	2020 IEEE	Artificial Intelligence based Recommendation System	Hybrid of content-based and collaborative filtering	Limited recommendation data for new users. Reduced accuracy with few user ratings.
11	Ravneil Nand, AnuragananD Sharma and Karuna Reddy	2018 IEEE	Skill-Based Group Allocation of Students for Project-Based Learning Courses Using Genetic Algorithm: Weighted Penalty Model	Genetic algorithm for skill diversity in groups	Computationally intensive. Binary skill responses may oversimplify abilities.
12	Subharag Sarkar and Manfred Huber	2021 IEEE	Personalized Learning Path Generation in E-Learning Systems using Reinforcement Learning and Generative Adversarial Networks	Reinforcement Learning and GANs for learning paths	Synthetic data may lack real-world complexity. Limited flexibility with predefined learner types.
13	Nikhil Chigali; Sai Rohith Bobba; K Suvarna Vani; S Rajeswari	2020 IEEE	OCR Assisted Translator	OCR with preprocessing and segmentation techniques	Depends on third-party services for translation. Handwritten text, requires considerable computational power.
14	Martin Lasonˇ and Ondˇrej Jakl	2010 IEEE	Role-based Access Control in Software Services: Theory vs. Practice	UML-based RBAC generation	Dependent on quality of UML diagrams. Miss's users in early design phases.
15	Saurabh Dome; Asha P Sathe	2021 IEEE	Optical Character Recognition using Tesseract and Classification	OCR techniques Python Tesseract	Accuracy is highly dependent on the quality of input. Limit performance on devices without sufficient computational resources

By integrating both content-based and collaborative filtering techniques into a hybrid system, this paper addresses the limitations associated with data sparsity and improves recommendation precision, offering a more robust solution for students with varying interests and backgrounds. In addition to hybrid filtering, the implementation of role-based access control (RBAC) within this paper significantly enhances its manageability. As noted by Lasoň and Jakl [14], RBAC ensures that users receive appropriate access to features based on their roles, which is in crucial in educational systems of where students, faculty, and administrators have distinct needs and responsibilities. By customizing recommendations based on user roles, the system can provide tailored suggestions that not only improve user engagement but also facilitate easier navigation and management of the application. This role-based approach helps in overcoming the shortcomings of previous systems, which often offered a one-size-fits-all solution. Another major advancement of this paper is the automated generation of academic reports. This feature addresses a significant gap in the current literature, where the need for efficient reporting systems in educational institutions has been recognized but not adequately fulfilled. Reports are generated weekly, summarizing students' progress, skills acquired, and participation in various activities, which aids in tracking academic performance over time. This automation not only saves time for faculty and administrators but also provides actionable insights for both students and institutions to inform curriculum development and resource allocation. By employing a hybrid filtering approach, utilizing NLP for skill extraction, and integrating role-based recommendations, this paper effectively mitigates the disadvantages identified in the literature. The combination of personalized course recommendations, improved user management through RBAC, and automated reporting positions this system as a comprehensive solution to the challenges faced by current educational systems. Through continuous learning and adaptation, the proposed system will ensure that students receive relevant recommendations tailored to their evolving skills and interests, ultimately enhancing their academic and professional development.

Conclusion

To conclude, this research on an AI-driven Academic Achievement Tracker has demonstrated its significant potential to revolutionize educational administration and learning experiences. The integration of AI and ML technologies into certificate management and recommendation systems has not only enhanced the efficiency and accuracy of academic data handling but also personalized the educational pathways for students based on their specific skills and accomplishments. Our exploration has highlighted the transformative impact of such systems in providing dynamic and adaptive learning environments that cater to the diverse needs of students and educators. The employment of hybrid filtering techniques, role-based access control, and machine learning algorithms such as decision trees and reinforcement learning for predictive analytics and personalized learning experiences embodies a substantial leap forward in educational technology. Moreover, the system's capability to automate and optimize academic record-keeping and generate insightful reports presents a compelling case for the broader adoption of similar technologies across other educational institutions. As educational demands continue to evolve, the continuous development and integration of advanced AI functionalities will be crucial in maintaining the relevance and effectiveness of academic systems. Future research should focus on refining these technologies to handle increasingly complex data sets and educational scenarios while ensuring that these systems remain accessible and beneficial to all educational stakeholders. This ongoing innovation will be vital in realizing the full potential of AI in education, ensuring that it remains a cornerstone of modern educational practices.

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