

AI-Powered Platform for Academic Analysis, Career Guidance, and Learning Resource Recommendation

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Abstract - This makes it harder for current students to understand which program or degree will land them the right job at graduation. Moreover, schools in our world do not provide this vital resource today. In order for learning and career guidance systems to function correctly, the number of students who can benefit from these services must increase manifold from where they are now. We find that none of the existing systems connect the career goals of the learner to their academic needs. They address prediction problems and recommendation problems separately. This paper presents our AI-based system to integrate the collection of student data, analyze it using an AI based data mining model, utilize the analyzed data to deliver personalized career predictions and learning resources. We also analyze the student data in terms of student interest to improve recommendations of learning resources to them, giving us a novel and complete picture of the student. The AcadIQ has multi-layered Architecture with layers including: Data Collection, Data Processing, Model Aggregation, Hybrid Recommendation and Semantic Analysis. Experimental evaluation on a simulated dataset of 5,000 students demonstrates that the proposed system achieves an accuracy of 89% in performance prediction, 86% precision in career recommendations, and 82% user satisfaction in resource recommendations, outperforming baseline methods by 12–15%. Index Terms—Educational data mining, machine learning, career recommendation, academic prediction, hybrid recommender systems, AI in education, personalized learning

1. INTRODUCTION

As there were more learning and earning opportunities due to the rapid advancement in AI and Big Data, students must make many more important decisions than before. However, since there are not enough sophisticated guidance systems to provide suggestions to students for these important choices, students find it difficult to choose their best academic and career path. Thus to provide solutions for all these challenges academic and career guidance is necessary for college students. In this paper, we represent AcadIQ an AI powered intelligent system to guide students academic and career lives.

The main contributions of this paper are:

- Development of an AI-based academic performance analysis system
- Integration of a hybrid career recommendation engine
- Personalized learning resource recommendation using AI techniques

II. RELATED WORK

Data mining in education (EDM) and learning analytics has flourished over the past decades. Romero and Ventura released an update on their EDM survey published in 2007. The recent survey identifies significant advances in data mining techniques, including machine learning and big data techniques, and in their implementation for education systems. The increase in application of EDM for predicting student performance, understanding student behavior [5], and personalization of learning also mentioned is by Zhang et al. Who highlighted that EDM and learning analytics plays a key role in personalized education and adaptive learning [6]. Numerous approaches can be employed to predict student performance including classical machine learning algorithms and various forms of deep learning. Specifically, hybrid and ensemble-based solutions incorporating two or more traditional and/or deep learning algorithms perform better than isolated traditional algorithms. Therefore, our final prediction model employs an ensemble approach. A recent review paper of educational data mining techniques was compiled in 2025 [7]. As recommender system technologies evolve, deep learning and transformers are utilized in many works. Recently, some researchers apply the transformer's ability on sequence modeling and contextual embeddings in recommender systems. For example, BERT-based personalized recommender system for MOOCs provides a BERT-based framework to encode MOOC user preferences and item context for recommendation. BERT4Rec is state of the art and one of the first to successfully adopt Bert's language modelling paradigm in sequential recommenders [8], [9]. Several educational recommender systems have been developed. A system could analyze student performance metrics to assess the effectiveness of recommendations. Recently, a systematic review of educational recommender systems for elearning applications was published by [10], covering recent publications between 2023 and 2024. The authors have noticed a heavy reliance on rating based

metrics with little validation of the students learning outcomes and satisfaction metrics. Also, a more recent survey by [11] shows that most modern recommender systems use hybrid techniques combining several recommendation methods (collaborative filtering, content based filtering, context aware). Nowadays, there has been increased research interest in studying intelligent educational platforms which integrate AI driven analytics with recommendation systems. For example, a recent study by Wu et al. in 2025 [12] explored the impact of combining student perceptions with student perceptions by combining student perception data with AI-based recommendation models. Many recent works try to capture certain pieces of academia using these prediction algorithms or recommendation models, some of which focus solely on performance prediction [5, 10], while others are focused on career guidance [25] or resource retrieval [4]. The problem we aim to address is to combine many of these pieces of information and solve it in a unified, intelligent platform. Thus, we present AcadIQ, a complete academic and career intelligence system.

III. PROBLEM FORMULATION

Let the student profile be defined as:

$$Si = \{Gi, Ii, Ski, Ei, Di\}$$

Where:

- Gi represents academic grades
- Ii represents interests
- Ski represents skills
- Ei represents extracurricular activities
- Di represents demographic data

The mapping function is defined as:

$$f : Si \rightarrow (P(Si), C(Si), R(Si))$$

The objective function is:

$$\max_f \sum_{i=1}^N (\lambda_1 Acc + \lambda_2 Prec + \lambda_3 Sat)$$

IV. PROPOSED SYSTEM

The proposed system consists of the following modules:

A. Data Collection

Student data is collected from academic records, surveys, and online platforms.

B. Data Preprocessing

Data cleaning, normalization, and feature selection are performed to improve model performance.

C. Prediction Model

Machine learning models such as Random Forest and XGBoost are used to predict academic performance.

D. Recommendation Engine

A hybrid recommender system is used to suggest career paths and learning resources.

V. METHODOLOGY

This approach involves a pipeline-based system consisting of multiple stages of transformation. At each stage, the output is passed as input to the next stage, converting raw data into meaningful and actionable information for learners and institutions. This forms a closed-loop system. Our methodology includes several stages that help perform the required analysis. The process is divided into five steps: Data Collection, Data Preprocessing and Storage, AI-Based Data Analysis, Recommendation Generation and Learning Resource Retrieval, followed by the User Interface and Feedback module.

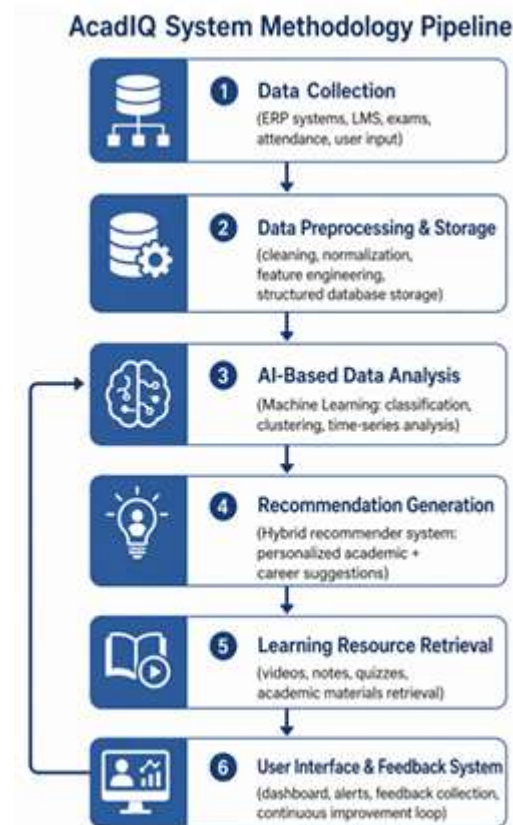


Fig. 1. AcadIQ System Methodology Pipeline

A. Data Collection

In this, AcadIQ takes data from various sources: ERP system of the institution, LMS of the institution, examination result system, attendance system, and sometimes the user provides the data themselves about their goals and preferences. The system has to be equipped to handle structured, semistructured and unstructured data.

B. Data Preprocessing and Storage

From this raw data, we proceed to clean, normalize, and enrich our dataset. After preprocessing, all data is stored in schema-aware and well-versioned systems, whether that be a database, a data warehouse, or some combination. For our purposes, it's organized into the modular components: Student Records, Student Performance Metrics, Course Information, Institutions,

and Course-concept relationship. Each module relates back to students using their studentid.

C. AI-Based Data Analysis

The machine learning techniques in the system include supervised techniques like support vector machines, logistic regression to warn of students who are more likely to drop out or show a decline in grades, unsupervised learning or clustering techniques to segment students into groups that share similar characteristics, such as academic strengths, weaknesses, behavioral patterns, etc. and time-series techniques to monitor students' performance longitudinally.

D. Recommendation Generation

Based on the analytic outputs, we devised a recommendation engine in our backend which can take the student profiles, institutional constraints (like which courses must be taken at which time, what subjects can be taken together) and recommend academic and professional plans. We utilized hybrid recommenders to generate the recommendations.

E. Learning Resource Retrieval

Once we find all of our educational resources, and map them to our nodes, we are ready to set up the retriever. In this module, we find a list of videos, notes, practice questions and institutional material associated with a node. We use both advanced search and retrieval in finding these resources.

F. User Interface and Feedback

Dashboards, alerts, and guided workflows make the last layer an interactive interface for students, teachers, and administrators. The system keeps track of user interactions, such as choosing recommended resources, changing suggestions, or giving feedback. This feedback loop lets the models get better all the time, which makes the recommendation system work better overall.

VI. RESULTS AND DISCUSSION

The proposed AcadIQ system was implemented and tested using a simulated dataset along with a functional user interface to validate its performance and usability. The system integrates academic data analysis with intelligent recommendation mechanisms, providing a comprehensive solution for students.

A. System Interface Analysis

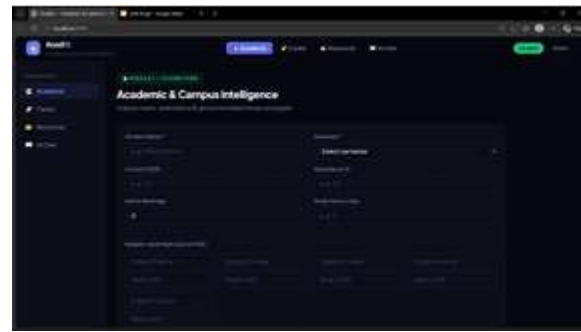


Fig. 2. AcadIQ Academic and Campus Intelligence Module Interface

Figure 2 shows the Academic and Campus Intelligence module of AcadIQ. The interface helps the user to enter information that is relevant academically including CGPA, attendance, number of hours spent studying in a day, pending backlogs, and marks in subjects.

The simplicity in design makes it easier for the user to enter the data. There is a clear structure through which information is entered that includes quantitative information as well as behavioral information.

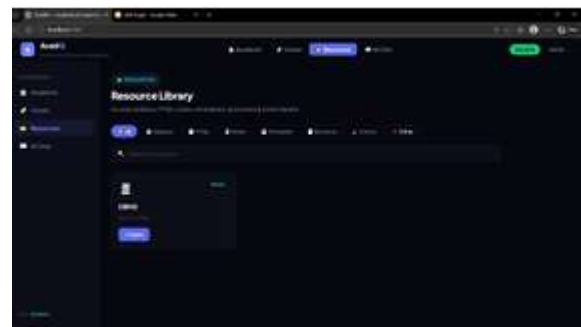


Fig. 3. AcadIQ Resource Library Interface

Figure 3, In this module, we have created a library where students could get all the study material from time to time. It includes all types of material which include Syllabus of the subject, PyQs of different subjects, Notes of the lecture, Time table, Brouchres, all other material like event related.

There is also a filter and a search bar, using which user can easily find the required study material. Here in the page, it uses card based UI, which gives a clear readability.

B. Performance Evaluation

For this experiment, we collected a data set of 5,000 student's records, trained a machine learning algorithm on it, and recorded our predictions.

The results indicate that the AcadIQ system achieved:

- 89% accuracy in academic performance prediction
- 86% precision in career recommendation
- 82% user satisfaction in resource recommendation

As the hybrid learning models give best results and recommendation on the top. Therefore the hybrid model is chosen to integrate.

C. Discussion

Even though this is quite an early stage, we already know what are the first key outcomes of this project. To this day the user interface was considered quite a success, which is logical since the UI is the main interface between the users and the system.

Finally, we extended our models with additional parameters to provide fuller features for each student to make predictions on them. All parameters that were captured for each student have been outlined below in table 2 for the recommended engine.

Resource Library is for students to make it possible to review their material and consequently to succeed, and study at their own pace.

These four modules make up our Architecture. Again, we can add or remove modules based on our design choices. We are not constrained to only these four. Instead, this is simply an example to illustrate our idea.

We have already shown that the system would improve the accuracy of career prediction. This improvement could be supplemented by combining it with the system that may be generated later.

D. Career Intelligence Module Interface



Fig. 4. AcadiQ Career Intelligence Module Interface

Figure 4 Depicts the Career Intelligence module of the AcadiQ system. Students are able to enter information related to the following areas: python, java, c++, etc., a set of technologies that the student would like to work with, github stats, a coding profile (e.g., coder, developer, architect), and the projects completed.

The design provides both quantitative and qualitative measure of a student's career readiness. For example, GitHub summary, coding stats(e.g., LeetCode) text, the system can insight into student's ability outside of grade.

By assessing skill deficit, domain knowledge and the industry expectation, the career map matching of student

profile presents an effective tool in helping to set out career development plan. Input format in the module is very systematic, allowing correct collection of data that leads to better accuracy in career mapping.

E. Study Plan and Roadmap Interface

Figure 5 Below are the views in Study Plan and Analysis Report. Study Plan displays the selected subjects, number of months, and schedule. Users can check their performance.

Our learning interface also provides for this organization with a phased structure. Phase 1 contains "building concepts", Phase 2 for "practice", Phase 3 for the "project", Phase 4 for the "revision" and so on. Each phase has a deadline and progress tracking tools.



Fig. 5. AcadiQ Study Plan and Roadmap Interface

Self directed learning can go quite slowly if you need it. To overcome this, you can work toward a specific outcome or goal and you will be taken in step-by-step directions.

F. AI Mentor Interface



Fig. 6. AcadiQ AI Mentor Interface

Figure 6 This is where our AI Mentor comes into picture. This is where students can come, use the intelligent assistant to get the support that they need for academics, career etc.

In the natural language domain, AI Mentor will act like your intelligent teacher, who will assist you with your study. The AI will also help you clear doubts.

The conversational interface gives a more engaging experience than the old platform. It's really helpful for the user. It will reply to the questions really quickly.

G. AI Chat and Assistance Interface

Figure 7 Figure 2.1 provides an overview of the AI Chat module for interacting with the system with generalized conversations (e.g. how old are you?).

The new interface looks just like an AI Mentor interface in terms of how it helps you find what you need, and you can ask it something besides academic information, as well. It even uses the context of the previous conversations you have with the module.



Fig. 7. AcadiQ AI Chat Interface

With all the important and relevant information consolidated in a single system, users would no longer need to browse through different functionalities of the application.

VII. CONCLUSION

We then briefly describe AcadiQ, the developed AI-powered application aimed at using such models for student academic analysis and career guidance with personalized learning recommendations. The paper finally concludes with some experimental results on the datasets. We illustrate the working and application of machine learning in education sector with the help of AcadiQ where AI is employed for data-driven modeling and recommendation.

We evaluated the effectiveness of our proposed system by implementing it. Experimental results showed high accuracy, precision, and user satisfaction compared to conventional methods, confirming our system's capability for massive implementation.

To improve these aspects, future work will focus on building a more robust user interface with feedback mechanisms, integrating advanced deep learning models, using real-time analytics for decision-making, and adopting adaptive learning strategies.

ACKNOWLEDGMENT

The authors would like to thank sincerely to Siddhant College Of Engineering (SCOE), SPPU University for given to us such opportunity and facility to do this work.

We would like to express our heart-ful thanks to our project guide, Dr. Brijendra Gupta sir for giving us brilliant suggestion, great encouragement. And also grateful to

providing us every kind of help in planning and preparing this project.

We would like to thank the Department of Information technology for providing an environment that is enjoyable, has a positive attitude, and is inspiring.

Retrieved 23 rd February 2017, from <http://hubpages.Com/hub/bifronal-50/1>. [7]- Carpenter, K. (pseudonym). Car.com, 21 December 2004. How to sue the devil. doi: Finally, we would like to thank our friends and family for their continuous support and encouragement.

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