Journal of Advances in Developmental Research (IJAIDR)

E-ISSN: 0976-4844 ● Website: www.ijaidr.com ● Email: editor@ijaidr.com

SMART ED: AN AI-POWERED EDUCATIONAL PLATFORM FOR PERSONALIZED LEARNING

Badiginchula Lakshmi Prasanna[1], Molakathalla Girija[2], Manjula Mohan Krishna[3], Kesamreddy Chenna Keshava Reddy[4], K.B.Sivarani[5]

[5]Guide
Department Of Cse
Tadipatri Engineering College,
Tadipatri

Abstract:
Artificial Intelligence (AI) is undergoing a revolutionary integration in the field of education that has the potential to completely reshape pedagogical approaches. The rise of personalized learning experiences, where AI aims to modify instructional materials and interactions to suit each learner's particular requirements, preferences, and speed, lies at the heart of this change. This study explores the many facets of AI-driven personalized learning, including how it might improve e-learning modules and the emergence of AI-powered virtual tutors that offer adaptive learning pathways and real-time support. These developments hold the potential to improve accessibility and engagement in education, assisting students in more successfully and efficiently achieving their academic objectives. But as digital innovations become more integrated into the fabric of education, it is critical to comprehend how AI may help personalize learning. In addition to the advantages, this integration brings up important ethical issues including algorithmic bias, data privacy, and the digital divide. It is essential to make sure that equity, transparency, and inclusivity are taken into consideration while designing and implementing AI applications in education. By taking care of these issues, educators and tech developers can use AI to make education more individualized, effective, and equitable, eventually creating a setting where all students have the chance to succeed.

Keyword: AI, education, personalized learning, virtual, real-time support, effective, equitable.

INTRODUCTION

A growing area called "educational data mining" uses sophisticated data mining techniques to examine educational data gathered from a variety of sources, including e-learning databases, student records, and academic achievement metrics. Effective methods for analysing this data include K-means clustering and K Nearest Neighbors (KNN), which use clustering, classification, and association rules to uncover insights. These techniques assist in identifying trends that characterize students' exam performance and other relevant information. To help educators make well-informed decisions to improve teaching strategies and student results, the data is first sorted and clustered to arrange it logically and enable deeper analysis. Educational institutions can obtain important insights about the behaviour and performance of their students by utilizing these data mining tools. For instance, KNN can identify students who might require extra support by comparing them to their peers, while K-means clustering might categorize students according to their performance levels. Teachers can modify their teaching strategies, offer focused interventions, and enhance the educational process overall with the help of these insights. Institutions can create a more productive and encouraging learning environment that promotes improved academic results and student growth by methodically analysing educational data.

RELATED WORK

Literature evaluation is a totally vital step inside the software improvement process. Before growing the device, it's miles crucial to determine the time element, price savings and commercial enterprise robustness. Once these things are glad, the next step is to determine which running gadget and language can be used to broaden the device. Once programmers start constructing a device, they want numerous external help. This support may be received from senior programmers, books or web sites. Before designing the system, the above concerns are taken into consideration to increase the proposed gadget.

The fundamental a part of the assignment improvement department is to very well have a look at and review all of the requirements of the challenge improvement. For every assignment, literature assessment is the maximum vital step within the software program development system. Time elements, resource necessities, manpower, economics, and organizational electricity need to be diagnosed and analysed earlier than growing the equipment and related layout. Once those elements are satisfied and carefully researched, the following step is to decide the software program specs of the specific pc, the operating machine required for the undertaking, and any software program required to transport forward. A step like growing tools and capabilities associated with them.

The study adds to our understanding of the variables influencing universities' pursuit of educational innovation. A thorough description and categorization of innovation drivers and obstacles are given, based on an examination of ten institutional situations from five European nations. The findings show some "disengagement" between managers of higher education institutions and their subordinates, as well as between these institutions and students, businesses, and education policy makers. Major innovation-related issues in higher education are examined and relevant, useful suggestions are made in light of the findings [1].

The entire academic community and society at large are significantly impacted by the decisions made by deans and university administrators. The survey results on which academic decisions they concern and the factors that go into them are presented in this study. To aid in decision-making, we forecasted graduation rates in an actual case study using machine learning methods. Our findings are supported by actual data from five undergraduate engineering programs at District University Francisco Jose de Caldas in Colombia. The confusion matrix and the receiver operating characteristic curve are used to compare artificial neural networks and support vector machines. The architecture and methodology of the algorithm are introduced [2].

This paper examines how blended learning (BL) affects students' academic performance in higher education. A statistical synthesis of research comparing student performance in BL conditions with standard classroom instruction was carried out through a meta-analysis ($k = 51$ effect sizes). Disciplines and the way teachers evaluate students at the end of the course are included as moderating factors. The findings indicate that, in comparison to conventional teaching techniques, BL exhibits a little summary effect ($g^+ = 0.385$, $p < 0.001$). In STEM fields, the mean effect size was much larger ($g^+ = 0.496$) than in non-STEM fields ($g^+ = 0.210$). However, there are no discernible variations between the weighted mean effect sizes for the one-moment and multiple-component end-of-course evaluation techniques. The results demonstrate that, in comparison to standard classroom instruction, BL is substantially linked to higher learning achievement among STEM-disciplined students. As a result, the results and their implications for further research are discussed in detail [3].

Uncertain professional goals, uncertain courses, a lack of academic challenge, difficulties adjusting or transitioning, low or unrealistic expectations, a lack of dedication, and subpar performance are the main causes of poor retention [4].

To get the data, a stratified sampling strategy was chosen. The term "e-learning," or "electronic learning," refers to educational materials or methods made easier by electronic technology with the goal of improving students' proficiency, general knowledge, and capacity for productivity in a global setting. There are drawbacks to conventional teaching strategies including distance learning and in-person instruction. The lack of funding, infrastructure, and other resources, such as qualified and experienced human labour, makes it harder to maintain educational standards [5].

EXISTING SYSTEM

Teachers manually forecast a student's character under the current system. Teachers frequently use only the student's grades to give feedback when parents come to the college to inquire about their child's behavior. This approach is constrained, though, as it solely takes academic achievement into consideration and ignores the student's participation in a variety of extracurricular activities. This conventional method ignores the student's complex personality and potential outside of the classroom. Teachers may thereby overlook crucial facets of the student's conduct, passions, and abilities. A more thorough approach that takes into account a number of variables, including extracurricular activities, attendance, and input from different sources, would give a better picture of the character and general growth of the kid.

Disadvantages

- Excessive Focus on Academics: The current system overlooks other facets of a student's personality and development in favor of an excessive emphasis on academic achievement as a gauge of character.
- Missed Opportunities for Student Development: The system might miss chances to foster and build talents in areas where the student might succeed outside of academics if it ignores the student's participation in extracurricular activities.
- Possibility of Miscommunication with Parents: Parents may not get a complete view of their child's strengths, shortcomings, and general growth when feedback is mostly focused on academic achievement. This could result in parents making uninformed decisions or raising concerns.

REQUIREMENT ANALYSIS

Necessity and Feasibility Analysis of Proposed System:

Creating an efficient, flexible, and scalable tool that customizes learning experiences for each student is the main goal of creating an AI-powered personalized learning platform. In order to provide individualized learning routes and improve overall educational achievements, this system will use cutting-edge AI technology to analyse learning habits and preferences.

PROPOSED SYSTEM

K-Nearest Neighbors (KNN), K-Means Clustering, and Naïve Bayes algorithms are integrated into an AI-powered personalized learning platform in the suggested system to provide individualized learning experiences. While K-Means Clustering divides students into comparable learning profiles to allow for targeted material distribution, the KNN algorithm is used to categorize students according to their learning preferences and performance patterns. By forecasting students' future learning requirements and performance patterns using historical data, the Naïve Bayes algorithm improves the platform even more. By integrating these strategies, the system seeks to improve engagement, learning results, and overall educational efficiency by offering real-time feedback, individualized recommendations, and accurate, adaptive learning pathways.

Advantages:

- High precision
- Increased Productivity
- The information needed to evaluate students can be found in educational databases.
- Data mining techniques are more useful for categorizing educational databases and for assessing a student's performance and problematic behaviour.

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- The training data is used to generate intelligible prediction rules.
- Best examination and analysis of student tests.

SELECTED METHODODLOGIES

- K Nearest Neighbor Classifier
- Naïve Bayes Classifier

K-NN is a kind of instance-based learning, often known as lazy learning, in which all computation is postponed until classification and the function is only locally approximated. One of the most straightforward machine learning methods is the k-NN algorithm. The neighbors are selected from a collection of objects for which the object property value (for k-NN regression) or class (for k-NN classification) is known.

Naïve Bayes is predicated on the idea that predictors are independent and is based on the Bayes Theorem. To put it simply, a Naive Bayes classifier makes the assumption that a feature's existence in a class has nothing to do with the existence of any other features. For instance, if a fruit is spherical, red, and roughly three inches in diameter, it can be categorized as an apple. All of these characteristics independently increase the likelihood that this fruit is an apple, which is why it is referred to as "Naive," even if they are dependent on one another or the presence of other characteristics.

The Naive Bayes model is especially helpful for very big data sets and is simple to construct. In addition to being straightforward, Naive Bayes has a reputation for doing better than even the most advanced classification techniques.

SYSTEM ARCHITECTURE

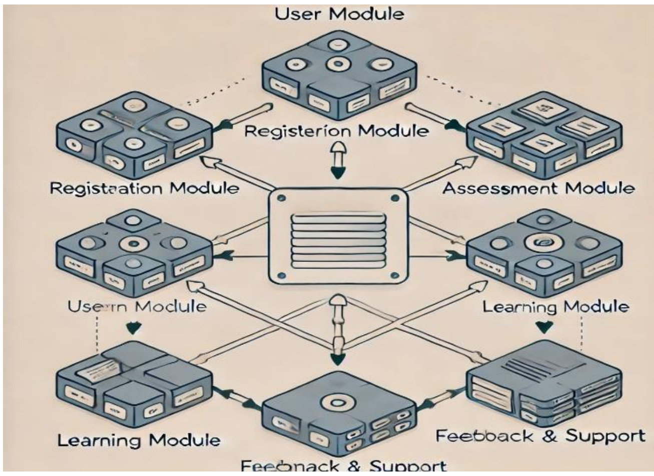

Fig 1: System Architecture

SYSTEM MODULES

- User Module
- Registration Module
- Assessment Module
- Learning Module
- Feedback and Support Module

Modules Description

User Module:

1. Login:

•Users access their accounts by entering their credentials (username and password). Successful login grants access to the personalized dashboard.

•The system verifies credentials against stored data. Incorrect information prompts an error message, and a link to the registration page is provided for new users.
2. Profile Management:
•Users can view and update their personal information, learning preferences, and settings.
•Allows users to edit their profile details, adjust learning preferences (e.g., preferred subjects, learning style), and manage account.

Registration Module:
1. User Registration:
•New users create an account by providing essential information such as full name, email, password, and contact number.
•Users fill out a registration form and submit it. The system validates input fields (e.g., ensuring passwords match, email format is correct). Successful registration directs users to the login page.
2. Validation and Confirmation:
•Ensures that all required fields are completed correctly and confirms user registration.
•Includes validation checks for field completeness, password strength, and valid email format. If validation passes, the registration is confirmed, and the user is notified of successful registration.

Assessment Module:
1. Assessment Creation:
•Educators create and configure assessments, including quizzes, tests, and assignments.
•Allows educators to design questions, set difficulty levels, and define assessment parameters. The module supports various question formats such as multiple-choice, short answer, and essays.
2. Evaluation and Feedback:
•Evaluates user responses and provides feedback.
•Automatically grades objective questions and provides instant feedback. For subjective questions, the system facilitates educator grading and comments.

Learning Module:
1. Adaptive Learning Paths:
•Adjusts learning paths based on user progress and performance.
•Dynamically modifies the sequence and difficulty of learning materials based on ongoing assessments and user interactions to ensure effective learning progression.
2. Interactive Learning Tools:
•Provides interactive elements such as quizzes, simulations, and games to enhance engagement.
•Integrates interactive tools that align with the content being studied, helping to reinforce learning through practical application and engagement.

Feedback And Support Module:
1. User Feedback:
•Allows users to submit feedback on their learning experience and the platform's functionality.
•Users can submit feedback through forms or surveys. The system collects and categorizes feedback for review by the admin.
2. Support Requests:
•Provides a mechanism for users to request help or report issues.
•Users can submit support tickets or request assistance with technical issues or content-related questions. The system tracks these requests and provides responses or solutions.

CONCLUSION

In this study, we used historical data and AI-powered personalized learning platforms to forecast student performance on a classification problem. We predicted student outcomes by looking at data like attendance, test scores, seminar participation, and assignment grades. To divide students into different performance groups, we used two classification techniques: the Naïve Bayesian Classifier and the Weighted Naïve Bayesian Classifier. By using these strategies, we were able to better customize educational resources and interventions to meet the needs of each individual student. The findings showed how AI may improve educational personalization by offering useful insights derived from predictive analysis. As time goes on, combining these AI-driven predictions with individualized learning techniques might greatly raise student accomplishment and engagement, transforming education to be more flexible and sensitive to the individual needs of every student.

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