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Adaptive Learning System using Machine Learning for Personalized Education

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Abstract- Online learning platforms have expanded rapidly in recent years; however, most existing systems still follow a uniform content delivery approach that fails to address individ ual learning differ-ences. Variations in learning pace, topic-wise understanding, and response behavior often result in reduced en gagement and ineffective learning outcomes. This paper presents an AI-based adaptive learning framework that personalizes educational resources by analyzing learner assessment data. The system integrates unsupervised clustering and supervised classification methods to catego-rize learners into three proficiency levels—Beginner, Intermediate, and Advanced—using features such as accuracy, response time, topic-wise performance, attempt frequency, and improvement rate. Ensemble learning techniques are employed to improve the accuracy of predictions and capture complex learning patterns. Based on predicted proficiency levels and identified weak areas, a hybrid recommendation mechanism dynamically adjusts question difficulty and provides personal ized learning materials, including instructional videos, reading content, and adaptive practice ex-ercises. Experimental evalu ation using standard classification metrics indicates increased learner engagement and measurable performance improvement following adaptive recommendations. The proposed framework offers a scalable and data-driven solution for personalized online education through constant observation and adaptive updates to support effective knowledge acquisition and long-term retention.

Keywords: Adaptive Learning, Machine Learning, Personalized Education.

I. INTRODUCTION

Online education has been growing rapidly due to inhouse classroom facilities, wide internet accessibility, and cost ef fective learning solutions. Additionally, the shift toward skill based, career-oriented education and the acceleration caused by the COVID-19 pandemic have significantly contributed to its global adoption. Online education gives students a lot of convenience like learning resources, time management, cost, travel free, etc. However, many online learning systems still follow a uniform instructional method in which the same learning material is provided to every student, without considering individual knowledge levels or learning speed. In practice, learners vary in their level of comprehension, learning pace, and thinking abilities. In reality, learners differ in their understanding capacity, learning pace, and thinking abilities.

Some people pick things up quickly, while others require some assistance. They may have to perform tasks repeatedly. They might need simple examples to get it. The problem is that a lot of online learning systems do not do a job of helping these people. When the work is too hard people can get confused. When the work is too easy people can get bored. Not want to do it. Learning systems also do not give people much feedback. They might just give you a score. Tell you that you finished something. This does not really help you see what you are good, at what you need to work on or how you are doing over time. To improve learning, learning systems ought to provide comprehensive feedback.

More individual learning platforms are created with the sup port of machine learning and ar-tificial intelligence. Learning platforms can analyze learner interaction logs, spot perfor mance patterns, and modify content to meet the needs of learners in order to create a customized learning platform. Adaptive learning systems do this by using ways to create a learning path that is just right for the learner. This path is determined by the learner's abilities and performance. Adaptive learning systems ensure that the learning path aligns with the student's progress and ability level. Because they enable students to learn in a way that works best for them, adaptive learning systems are beneficial to learners.

The proposed study introduces an AI-based adaptive learn ing system that evaluates student performance using factors such as accuracy, response time, and topic wise results. The system finds learning gaps and recommends relevant learning resources to aid in improvement by taking this evaluation into account. The main aim is to enhance learning effectiveness, raising student engagement, and creating more individualized and efficient online learning.

II. RELATED WORK

Adaptive Learning Systems in Online Education

Adaptive learning systems are used to create a person alized learner experience by taking into consideration the characteristics of each individual. Some of these characteristics include prior knowledge, rate of learning, and performance trends among others. The initial adaptive learning systems were rule-based and utilized pre-defined decision trees as well as static instructional paths. Although this was a huge step forward to provide a more personalized learner experience, the challenges faced in many instances from these systems were not being able to adapt at the same rate as the learner's experience based on current real-time behavior. More recently however, new enhancements have seen the incorporation of data-driven methodologies such as educational data mining (EDM) to use the data from the learner's interaction to determine behavioral patterns and forecast academic success rates. Romero and Ventura (2016) provide a great example of how this new form of analysis can be utilized to improve the adaptive learning experience, providing relevant evidence of the important role educational data mining plays in detecting behavioral patterns and forecasting learner success based on the learner's interaction with the system.

While the improvements made to improve personalization have significantly increased the over-all effectiveness and per sonalization of adaptive learning, many existing systems still rely heavily on static measures of performance such as a learner's final grade rather than incorporating current data of learner behavior like their response time or number of times a learner has attempted the same question.

Machine Learning-Based Student Performance Assessment

Prediction of student performance and identification of at risk learners has been accomplished through various ma chine learning prediction methods, including Decision Trees, Support Vector Machines (SVM), and Logistic Regression. However, it was proven by Hastie et al. that ensemble methods (e.g., Random Forest and Gradient Boosting) usually provide superior modeling results than individual classifiers when dealing with non-linear relationships between frame charac teris-tics. Examples of research by Huang and Fang confirm that using machine learning techniques to develop behavioral and academic models greatly improves the predictive ability of these types of algorithms as compared to more traditional approaches. However, many prior studies rely heavily on cumulative academic scores and demographic variables, while limited attention has been given to integrating fine-grained features such as response time, topic-wise accuracy, and improvement rate over time.

Recommendation Systems in Personalized Learning

Recommendation systems play a crucial role in modern online learning platforms by suggesting relevant learning materials such as instructional videos, practice exercises, and reading resources. Collaborative filtering and content based filtering are the two most commonly used approaches in educational recommender systems. As discussed in the Recommender Systems Handbook, hybrid recommendation strategies often provide superior results by combining multiple filtering techniques. While recommender systems have improved learner en gagement, most educational implementations focus on content similarity rather than learner proficiency level. They often lack mechanisms to dynamically adjust difficulty levels based on continuous performance monitoring.

Gaps Addressed by the Proposed Study

Although significant progress has been made in adaptive learning, several limitations still exist in current approaches. Behavioural metrics such as learner response time and the number of quiz attempts are often utilized only to a limited extent during learner evaluation. Similarly, clustering techniques are generally not employed to group learners with similar performance characteristics, reducing the effectiveness of personalized instruction. In addition, many existing systems do not continuously update their machine learning models to support ongoing personalization, and histor-ical learner improvement trends are rarely incorporated as decision-making features for adaptive learning.

The proposed research addresses these limitations by integrating supervised classification and unsupervised clustering techniques within a unified framework. Furthermore, the proposed system combines real-time performance monitoring with personalized recommendation strategies to cre-ate a more effective adaptive learning environment that enhances learner achievement, increases student engagement, and promotes long-term knowledge retention.

III. DATASET AND FEATURE ENGINEERING

Data Sources and Collection

The dataset used in this study was collected from learner interactions within an adaptive learn-ing platform that personalizes educational content according to individual learner needs. The col-lected data represent learners' academic performance, learning behaviour, and assessment activities throughout the learning process. The dataset includes student assessment information such as quiz scores, correctness of responses, and the difficulty level of attempted questions. In addition, inter-action logs record learner behaviour by capturing response time, the number of quiz attempts, and the duration of each learning session. The dataset also contains learning content usage information, including access to instructional videos, study notes, and practice exercises, which helps evaluate learner engagement with edu-cational resources. Furthermore, learner profile information, such as the enrolled course, subject domain, and prior knowledge level, is incorporated to provide a comprehensive representation of each learner. All data are collected automatically during learner interactions with the system, and appropriate anonymization techniques are applied to protect learner privacy and ensure data confi-dentiality.

Target Variable Definition

The primary objective of the proposed adaptive learning system is to classify learners according to their proficiency level while identifying individual learning weaknesses that require additional attention. Based on learner performance, the system categorizes learners into three proficiency levels: **Beginner, Intermediate, and Advanced**. This classification is performed using machine learning techniques that analyse behavioural and academic performance indicators. The predicted proficiency level enables the system to dynamically adjust assessment difficulty and provide per-sonalized learning resource recommendations that align with each learner's knowledge level and learning requirements. Consequently, the proposed framework supports individualized learning by delivering appropriate educational content and improving the overall learning experience.

Feature Engineering and Preprocessing

Table 1: Extracted Features and Educational Rationale

Feature Type	Description	Educational Rationale
Accuracy	Percentage of correct answers	Measures conceptual understanding
Response Time	Time taken per question	Indicates confidence and fluency
Topic-wise Score	Performance per topic	Identifies weak and strong areas
Attempt Count	Number of retries	Reflects difficulty perception
Session Duration	Time spent per session	Engagement indicator
Difficulty Level	Level of questions attempted	Measures learner capability
Improvement Rate	Score change over time	Learning progress indicator

Preprocessing Steps: Before training the machine learning model, the collected data were pre-processed to improve data quality and model performance. Missing values were handled by replac-ing them with appropriate mean or median values, depending on the distribution of each feature. Numerical features were standardized using feature scaling to ensure that all variables contributed equally during model training. Categorical variables, including learner proficiency labels, were encoded into numerical representations to make them suitable for machine learning algorithms. In addition, noisy and irrelevant records, such as extremely short or inactive learning sessions, were removed to improve the reliability and consistency of the dataset. These preprocessing steps ensured that the data were clean, balanced, and suitable for accurate learner proficiency prediction.

IV. METHODOLOGY

Data Collection and Assessment

The new learning system that uses intelligence starts by gathering information, about how learners interact with it. This happens when learners take tests on the website that are divided into topics and difficulty levels. These tests keep track of how the learners do including whether they get the answers right how long it takes them to answer each question, how hard the questions are and how well they do on each topic. The artificial intelligence learning system uses this information to get a picture of what the learners know and how they learn. The artificial intelligence learning system looks at all this data to understand the learners and their behavior.

Feature Extraction

To construct learner profiles, quantitative performance features are extracted.

Table 2: Assessment Structure in the Adaptive Learning System

Component	Description	Role in System
Topic Module	Subject-wise question grouping	Enables topic-level evaluation
Difficulty Level	Easy, Medium, Hard categorization	Supports adaptive progression
Timed Response	Question time tracking	Measures learner efficiency
Performance Logging	Stores attempt-level data	Enables learning analytics

Topic-wise accuracy is computed as:

$$Accuracy = \frac{\text{Number of Correct Responses}}{\text{Total Questions Attempted}}$$

Average response time is calculated as:

$$AvgResponseTime = \frac{\sum_{i=1}^{n} Time_i}{n}$$

A weighted performance score is defined as:

$$PerformanceScore = \alpha(Accuracy) + \beta(1 - NormalizedTime)$$

where $\alpha + \beta = 1$, and α and β represent the weighting coefficients.

Machine Learning Model

A classification model is employed to categorize learners into three proficiency levels: Beginner, Intermediate, and Advanced.

The classification function is represented as:

$\hat{y} = f(x)$

where x denotes the feature vector and $\hat{y}$ represents the predicted proficiency class.

K-Means clustering is additionally utilized to identify groups of learners with similar behav-ioral patterns.

Recommendation Engine

A hybrid recommendation approach is used according to the predicted learner proficiency level and identified weak areas of knowledge.

The recommendation rules are defined as follows:

- Accuracy < 60% → Basic learning resources
- Accuracy between 60% −80% → Intermediate practice
- Accuracy > 80% → Advanced exercises

The system uses outputs from both the clustering and classification algorithms to provide per-sonalized learning paths for each learner. The learners will be clustered based on their behavior similarity using clustering algorithms, and then specific types of content will be recommended to them such as instructional videos, reading materials, and adaptive practice exercises based upon their similar behavior clusters.

Learner profiles are updated dynamically and learner performance is monitored by a continuous feedback mechanism. To ensure better personalization and flexibility over time, the recommenda-tion engine periodically retrains the machine learning models.

Evaluation Metrics

The performance of the proposed system is evaluated using standard classification metrics like accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics help assess the effectiveness of learner classification and the standard of personalized recommendations.

Table 3: Confusion Matrix Example

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

System Architecture Overview

The various components of the AI-based adaptive learning system are interdependent. It has a website that learners can use to look at learning stuff take tests and see what the system thinks they should do next. The test part of the system checks what learners answer. Sends the results to a big database. The data processing layer processes the assessment data through pre-processing and fea-ture extraction. The extracted features are received by the ML Engine, which includes a classifier and a clustering algorithm to process the learner assessment data and produce learner proficiency levels and identify areas for the learner to improve. Based on this analysis, the recommendation module suggests personalized learning resources and dynamically adjusts learning difficulty.

A continuous feedback mechanism updates learner profiles and supports adaptive learning over time. In addition, the system integrates a trained machine learning pipeline in which preprocessing objects, including feature scaling and encoding components, are serialized to ensure consistent transformation during inference. Multiple supervised classification models and a clustering model are deployed to generate real-time proficiency predictions and learner segmentation. Model outputs and analytical statistics are stored in structured formats to support evaluation, reproducibility, and continuous system improvement.

V. RESULTS AND DISCUSSION

Model Performance Evaluation

The performance of the proposed AI-based Adaptive Learning System was evaluated against a set of standard performance metrics including classification accuracy, precision and recall. The performance of multiple machine learning models was tested to evaluate the ability of the models to predict the level of proficiency for learners.

Ensemble based models such as Random Forest and Gradient Boosting outperformed tradi-tional baseline models with respect to prediction accuracy and consistency based on the experi-mental results. The use of these models also exhibited a greater ability to capture complex learning patterns and the behavioral variability of students. The higher precision and recall values obtained when using the classification framework provide further evidence of the reliability of the usage of the framework to identify learner proficiency levels. The experimental results provide strong evidence that the use of ensemble learning methods will provide improved predictive performance, and thus may be applicable to use in adaptive learn-ing environments. The comparative performance of the models evaluated is illustrated by the Fig. 1.

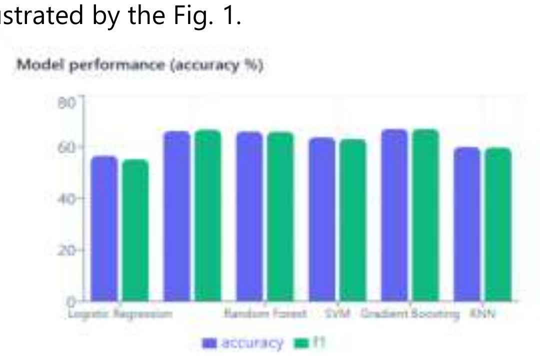

Figure 1: Comparison of classification accuracy across different machine learning models.

Learning Efficiency Analysis

A correlation analysis of learner accuracy and response time was performed to determine how efficacious learning occurred. A negative correlation was found between learner response times and accuracy; increased learner response time was related to a decrease in learner accuracy. Therefore, it can be inferred that those learners who have a better conceptual understanding of the task respond faster and more accurately than learners who do not have a strong conceptual grasp of the task.

The relationship between learner progress over time and accuracy is shown in the Fig. 2.

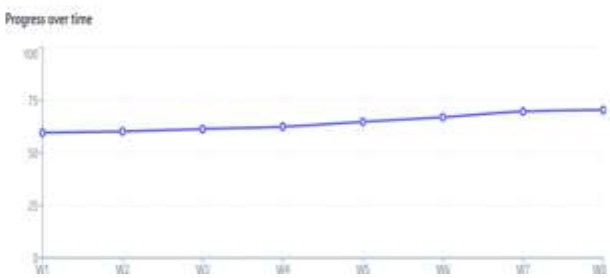

Figure 2: Correlation between progress over time and accuracy.

Adaptive Recommendation and Learning Improvement Analysis

Based on their performance on assessments, the system was able to identify each learner's level of knowledge/understanding of the subject matter as well as their areas of weakness. It also grouped together learners who exhibited similar learning styles so that it could provide them with improved recommendations. The system is different from learning systems that give everyone the same material. This system changed the difficulty of the material and the way it was presented based on what each learner needed. This made learning more interesting and effective for the learners. The system was tested times to see if it was working. The results showed that learners did better on tests after they got recommendations.

The improvement in learner performance is illustrated in Fig. 3.

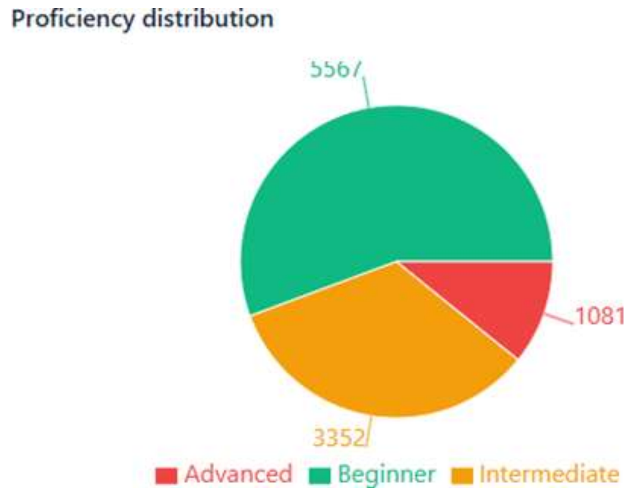

Figure 3: Improvement in learner performance after adaptive recommendations.

The results show that changing the material in time and constantly checking how learners are doing makes a big difference in how well they learn.

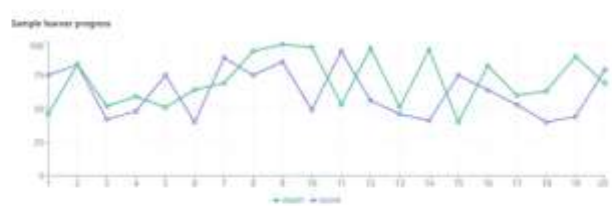

Figure 4: Sample Learner Progress

The system helped learners spend time on things they already knew and more time on things they were bad at which made the learning process better. The system is good, at helping learners because it gives them recommendations and it always checks how they are doing. The learner performance is what the system is trying to improve. It does this by giving them adaptive recom-mendations.

Discussion

The adaptive learning framework we propose works well because it combines machine learning with a strategy to assess learners in a way. This helps make education fit each learners needs. Unlike conventional learning systems that provide identical content to all learners, the proposed system dynamically adjusts question difficulty based on learner accuracy and response time. This adaptive mechanism ensures that learners receive questions appropriate to their current proficiency level, thereby improving engagement and reducing unnecessary learning difficulty.

The Random Forest classifier does a job of predicting how well a learner is doing. It looks at things like quiz scores how times they try a quiz how long they take to respond how often they complete assignments, how much they participate in forums and how they do on specific topics. Based on this the system gives learners personalized advice on what to focus on. Finds areas where they need to improve. These results show that using machine learning with assessment can really make online learning fit each learner better.

Even though our framework shows promise we have only tested it with a set of educational data. We plan to work on validating it with larger real-world data. We also want to try advanced machine learning techniques, like deep learning and reinforcement learning and use explainable AI to make our recommendations clearer and more effective.

VI. CONCLUSION

An AI-powered adaptive learning system that tailors instructional materials according to each learner's performance was presented in this study. The system dynamically creates learner pro-files and divides students into various proficiency levels by evaluating assessment data, including accuracy, response time, and topic-wise performance. Learning gaps were successfully identified and specific learning resources were suggested using machine learning techniques, such as classi-fication and clustering.

The experimental results show that personalized learning really helps people get more inter-ested in what they're learning. It also helps them not waste time on things they already know. This kind of learning makes their overall performance, in school better. Unlike the way of teaching where everyone learns the same thing personalized learning is different. It helps learners focus on what they need to learn. It saves them time because they do not have to learn things they already know. Personalized learning makes learning fun and helps people do better in school.

Learning platforms, the proposed system continuously adapts to learner progress, providing meaningful feedback and customized learning paths. This makes the system suitable for modern online education environments where learner diversity and flexibility are essential.

VII. FUTURE SCOPE

The proposed AI-based adaptive learning system has the potential to be further improved via the use of machine learning and deep learning technologies, thereby increasing both the ability to predict learning outcomes and the ability of the learner to learn. Future research should look into the use of neural networks or reinforcement learning, as they will be able to construct a real-time changing learning path for individual learners by analyzing their immediate behavioral pattern while they are engaged in learning. Additionally, more analytical techniques to assess student involvement and engagement will help us better comprehend and create content that will enable our students to succeed. By providing adaptive-based learning with the ability to integrate with mobile, there will be even more learners actively engaged in learning than ever before.

Furthermore, the incorporation of natural language processing (NLP) will create the basis for an Intelligent Tutor (and Automated Feedback) within adaptive-based learning, allowing the learner to reach performance levels beyond their prior experience or expectations.

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