A STUDY ON THE APPLICATION OF DEEP LEARNING AND MACHINE LEARNING IN ADAPTIVE INTELLIGENT TUTORING SYSTEMS

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Abstract
The Intelligent Tutoring Systems (ITS) are now regarded as one of the pillars of modern educational technology, offering a personalized experience in education, adapting to the needs of individual students. The paper addresses the use of ML algorithms in adaptive ITS and how they can be used to create better learning experiences, student interactions, and system efficiency. The paper will examine various machine learning methods, including supervised learning, reinforcement learning, and neural networks, which have been used in ITS. Also, it covers the issues, assessment techniques, and research directions of adaptive intelligent tutoring systems. The Intelligent Tutoring Systems (ITS) are an essential factor in providing individualized education with the help of adaptive learning technologies. Modern ITS has been greatly improved in adaptability and intelligence due to the combination of Machine Learning (ML) and Deep Learning. This paper examines the application of supervised, unsupervised, reinforcement, and deep learning methods in adaptive ITS. Decision Trees, SVM, and Random Forests are supervised models that are applicable in predicting student performance with an accuracy of up to 90. Unsupervised algorithms such as K-Means clustering can be used to define the behavioral patterns of learners to aid in personalized teaching. Reinforcement Learning is a process of maximising tutoring strategies by the use of reward-based policy improvements. Deep Learning methods, especially Deep Knowledge Tracing using LSTM, are effective in structuring temporal learning styles with a greater AUC of more than 0.85. The

study puts emphasis on student modeling, involving knowledge tracing and learner profiling, in adaptive systems. Adaptive techniques are reviewed, such as dynamic feedback, content sequencing, which is personal, and real-time assessment. An integrated ITS architecture, based on the use of ML, includes student, tutoring, and analytics modules. The measures of evaluation are the learning gain, the rate of engagement, and the accuracy of prediction (RMSE, MAE). 20-25 percent learning increase by ML-based adaptive conditions when applied. Issues with implementation, such as data privacy and real-time scalability, are also discussed in the study. Afterwards Explainable AI model and multiple models for further personalization are used. All in all, ML-driven ITS proves to have great opportunities of scalable, data-driven, and exceptionally personalized educational system.

1. Introduction

The need to receive individual education has had an enormous increase as the usage of e-learning websites is increasing [1][2]. The conventional systems of education are usually not able to support the individual differences of learner such as previous knowledge, learning speed and cognitive capability [3]. ITS overcome this problem by offering flexible learning environments to students [4]. The accelerated development of Artificial Intelligence (AI) and Machine Learning (ML) has transformed the environment of educational technologies in the sphere of the Intelligent Tutoring Systems (ITS) development significantly [5][6]. Conventional e-learning systems usually carry pre-recorded content and standardized learning processes, which restrict their capabilities to cater to the differences in learners [7]. Conversely, ML-based ITS allows personalisation to be dynamic by modelling student behaviour and predicting learning outcomes as well as changing instructional strategies in real time [8][9]. The systems can create a one-to-one tutoring effect as they constantly evaluate the data of students and optimize their pedagogical decisions [10].

Modern adaptive ITS is based on the computational power of Machine Learning. Decision Trees, Support Vector Machines (SVM) and Random Forest Supervised learning algorithms make use of labelled historical student data to determine performance results (e.g., pass/fail, high/low achievement) [11-14]. These models allow identifying at-risk students early and providing evidence-based intervention approaches by determining the limits of making decisions based on elements like study time, quiz performance, and engagement [15]. Besides, unsupervised learning methods, such as K-Means and DBSCAN clustering, are used to uncover latent patterns in student learning behaviors without specifying them [16][17]. These models cluster students in terms of engagement, frequency of interaction and activities involved in learning, bringing out particular learner profiles of highly-engaged, moderate and passive learners [18]. This type of clustering will help to design personalized instructions and provide specific pedagogical assistance [19]. According to this paradigm, the tutoring system is an agent that will choose the instructional actions, like giving hints, quizzes, or explanations, according to a reward mechanism depending on increased student performance [20][21]. Through repeated learning cycles, the system will optimize its policy to maximize the sum of the rewards and thus improve adaptive teaching legislation and student performance [22]. More so, modeling of the intricate student-knowledge interactions has been made possible through deep learning approaches. Deep Knowledge Tracing is one of the techniques that enable ITS to approximate the state of knowledge in a learner over time to enhance the adaptive sequencing of content and prediction of mastery [23]. These are techniques that help modeling students in a fine manner that is critical in individualized learning journeys [24]. Student modeling, which includes knowledge tracing, learner profiling, and learning analytics, is a critical part of the ML-based ITS. ITS systems create detailed profiles of learners by tracing levels of mastery, patterns of responses, the amount of time spent on tasks, and answer accuracy [25]. Live learning analytics also make it possible to predict performance and identify dropout risk, which can be used to intervene in time [26]. Strategies based on ML models are adaptive learning strategies, customized content delivery, dynamic feedback generation and adaptive assessment [27][28]. These strategies manipulate the difficulty of questions, the time of hints, and the sequence of instructions, depending on the actual performance results, and improve the engagement levels and learning performance [29][30]. System-wise, the different modules that may be integrated with ITS architectures to support the integration of ML include: an interface layer to communicate with students, knowledge representation, behavior tracking, adaptive logic, student model, a tutoring model, and a data analytics module to predict and monitor. It is possible to personalize students and tutoring modules with ML algorithms, which are scalable and intelligent [31][32]. Although these developments exist, a number of challenges are still present, such as data privacy, real-time processing limitations, and compatibility of heterogeneous ML models, as well as the possibility of having explainable AI to make decisions that are adaptive to ensure transparency [33]. Machine Learning has transformed Intelligent Tutoring Systems by making them predictive and adaptable in content delivery and automated optimization of instructional techniques [34]. Modern systems can provide personalized, scalable, and data-driven education by incorporating the concepts of supervised, unsupervised, reinforcement and deep learning systems into ITS architectures [35-36]. This study will examine the underlying ML methods, student modeling algorithms, adaptive approaches, system designs and evaluation schemes, all of which make up next-generation adaptive ITS. Machine Learning allows the ITS to learn through interactions and encourages dynamism in teaching and enhances the accuracy of student modeling, learning outcomes prediction, and recommendation of learning paths.

Objectives

- Search for the use of ML in adaptive ITS.
- Name the ML algorithms that are typically applied in ITS.
- Look at the ways of personalization and learning improvement with the help of ML.
- Review problems and areas of research in the future.

2. Literature Review

2.1 Traditional ITS Approaches

Old ITS used rule-based systems and a cognitive tutor to have personalized instruction. Rule systems are based on the logic of if-then and thinking by cognitive tutors is modeled [36][37]. Early ITS was based on rule systems and cognitive tutors. Rule-based ITS are based on if-then rules to determine the content delivery, e.g., the GUIDON system [38]. The model tracing or production rules are used to model student cognition by cognitive tutors, e.g., the Carnegie Learning Cognitive Tutor [39]. Anderson et al. in 1995 tested the Cognitive Tutor in the middle school math; the students' learning was found to improve by 23% as compared to the usual learning. VanLehn in 2011 compared human tutoring, ITS and a non-adaptive system; ITS offered 85-percent of human tutor effectiveness. Clancey, 1987, GUIDON rule-based medical tutor; the adaptation was based on knowledge encoding by experts.

2.2 Machine Learning in ITS

ML has helped ITS to learn the behavior of students to make Predictive modeling of performance, Real-time adaptation [40], and Personalized content recommendation. ML enables ITS to be informed by the student behavior in [41]: predictive modelling, adaptive content, and dynamic feedback [42]. ML techniques consist of supervised, unsupervised, reinforcement, and deep learning.

2.3 Recent Studies

Huffernan and Heffernan carried out a powerful study on the application of Bayesian Knowledge Tracing (BKT) as part of the ASSISTments program to forecast the level of mastery of mathematics among students. They worked on modeling student learning as a probabilistic process whereby the knowledge acquisition varies with time [43]. BKT uses previous knowledge, learning rate, probability of guessing a skill and probability of slipping to get an estimation of the chance that a student has mastered a certain skill [44]. The model is dynamic and can change mastery beliefs following every student response and then generate instructional content that can be adjusted to suit the system [45]. This probabilistic method will allow taking care of troubled students in time and taking timely measures. Their study indicated that the performance of mastery prediction increases with the inclusion of fine-grained skill tagging and real-time response data [46][47]. The paper has emphasized the need to have the student data over a long time to ensure consistency in the knowledge estimation. Findings indicated a great enhancement in predicting student success as compared to non-dynamic approaches of assessment. The adaptive feedback created with the help of BKT increased the learning effectiveness and minimized the redundant repetitive learning of mastered concepts [48]. Moreover, scalability was the focus of the research because BKT models apply to large-scale educational data. Their results helped in the common use of probabilistic student modeling in ITS research [49]. On the whole, this research made BKT a trigger method of mastery prediction in adaptive learning [50].

Pardos and Heffernan examined how logistic regression models can be used to enhance adaptive feedback in Intelligent Tutoring Systems. Their study was to determine the probability of a student getting a question right on the basis of historical performance. Supervised learning method involved the use of logistic regression that was used to model the relationship between student characteristics, including the previous correctness, time spent, and attempts to future [51]. The ITS could know when to give hints, extra explanations, or more difficult problems by estimating the probability of success [52]. This predictive modelling technique improved the decision-making process in the tutoring system. The experiment demonstrated that the logistic regression provides a compromise between interpretability and predictive accuracy. The ML-driven system was more accurate in the prediction of student responses compared to rule-based systems. The authors noted that with data-driven models, it is possible to adapt them more flexibly than with manually crafted rules [53]. Their findings showed more individualization and greater correspondence of the timing of the feedback with the needs of the students. Moreover, the study demonstrated the relevance of developing predictive models through continuous data collection. The paper has played a major role in incorporating statistical ML models in adaptive learning systems. In general, it showed that real-time instructional adaptation can be supported successfully with the help of logistic regression [54].

Feng et al. explored how deep learning, especially in the form of neural networks, could be utilized in adaptive tutoring systems to automatically model the students. Their contribution overcame the constraints of the classical probabilistic models by tapping into the capabilities of deep neural networks to provide more complex and nonlinear relationships between educational data. The models that were used in the study included Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks with the aim of tracking student learning sequences with time [55]. These models were effective in terms of capturing temporal dependencies in the responses of the students to enhance the prediction of the knowledge state. The authors have shown that deep learning models have higher performance than the conventional Bayesian Knowledge Tracing even in large-scale data. The suggested method automatically learned feature representations without involving a large amount of manual feature engineering. The findings of the experiment revealed greater AUC and better accuracy in predicting the future student performance. Another advantage of deep models that was identified by the study is the capability to scale to massive online learning sites. Nonetheless, the authors have identified nuisances like the requirement of a huge data set and less interpretability. Their work helped to further the Deep Knowledge Tracing (DKT) as a strong alternative to classical student modeling methods. The results highlighted how deep learning has increasingly become important in next-generation adaptive ITS. In general, the paper has shown that neural networks can increase predictive accuracy and personalization in the education system to a considerable degree [56].

Table 1:Comparison of ITS Approaches with ML Integration

Approach	Adaptivity	ML Used	Scalability
Rule-Based	Medium	None	High
Cognitive Tutor	High	Minimal	Medium
ML-Based ITS	High	Supervised, RL, Deep Learning	High

Table 2: Comparison of ITS Approaches with ML Integration with Results

ITS Type	ML Algorithm	Dataset	Outcome
Cognitive Tutor	Bayesian Knowledge Tracing	Middle school math	23% improvement in learning
ASSISTments	Logistic Regression	Math exercises	Accurate mastery prediction
RL-based ITS	Q-learning	STEM tasks	Optimized hint delivery
Deep Learning ITS	LSTM/DKT	Programming exercises	High prediction accuracy

Machine Learning Algorithms in ITS

Table 3: Machine Learning Algorithm with Applications and Advantages and Disadvantages

ML Technique	Example Algorithm	Application	Pros	Cons
Supervised	Decision Tree	Predict mastery	Easy to interpret	Overfitting risk
Supervised	SVM	Performance prediction	High accuracy	Complex tuning
Unsupervised	K-Means	Cluster learners	Simple	Sensitive to initialization
Reinforcement Learning	Q-Learning	Adaptive hints	Learns optimal policy	Requires exploration
Deep Learning	LSTM/DKT	Knowledge tracing	Captures temporal dependencies	Needs a large dataset

Zhou and coauthors suggested a new knowledge tracing model, Cuff-KT, in 2025 to deal with the problem of real-time learning pattern adjustment (RLPA) in Intelligent Tutoring Systems (ITS). The conventional methods of tracing knowledge usually consider the development of learners to exhibit a given pattern depending predominantly on the previous work, which is not always the case since student learning patterns change depending on various factors such as motivation change or loss of mental energy. This tuning-free functionality allows the system to easily able to change in relation to the variability of learning behaviors and, in principle, be able to capture irregular learning dynamics that cannot be captured by traditional models. Experimental outcomes with several real-world datasets showed that Cuff-KT was by a significant margin able to increase the performance of different kinds of KT models by an average of 10 percent when applied to intra-learner shifts and by an average of 4 percent when applied to inter-learner shifts with low computational costs [57]. These findings demonstrate the capability of Cuff-KT to make better and prompt predictions of student knowledge states that can increase the responsiveness and effectiveness of adaptive systems of tutoring. The management of RLPA in the study provides a critical background to the next generation ITS, which will be capable of adapting individualization strategies dynamically within real learning environments [58].

3. Machine Learning Techniques in ITS

3.1 Supervised Learning

Purpose: Use techniques Decision Trees, Support Vector Machines (SVM), Random Forests and sample scenarios to predict student performance and learning outcomes based on the use of input features such as Study time, quiz scores. Pass / Fail performance or High / Low are the output labels. Decision boundary revealing student success prediction by a classifier. Regions are the categories of performance that are predicted and Dots are individual students. The model is trained with historical data that is labeled. DT, SVM and RF are used for prediction [59][60].

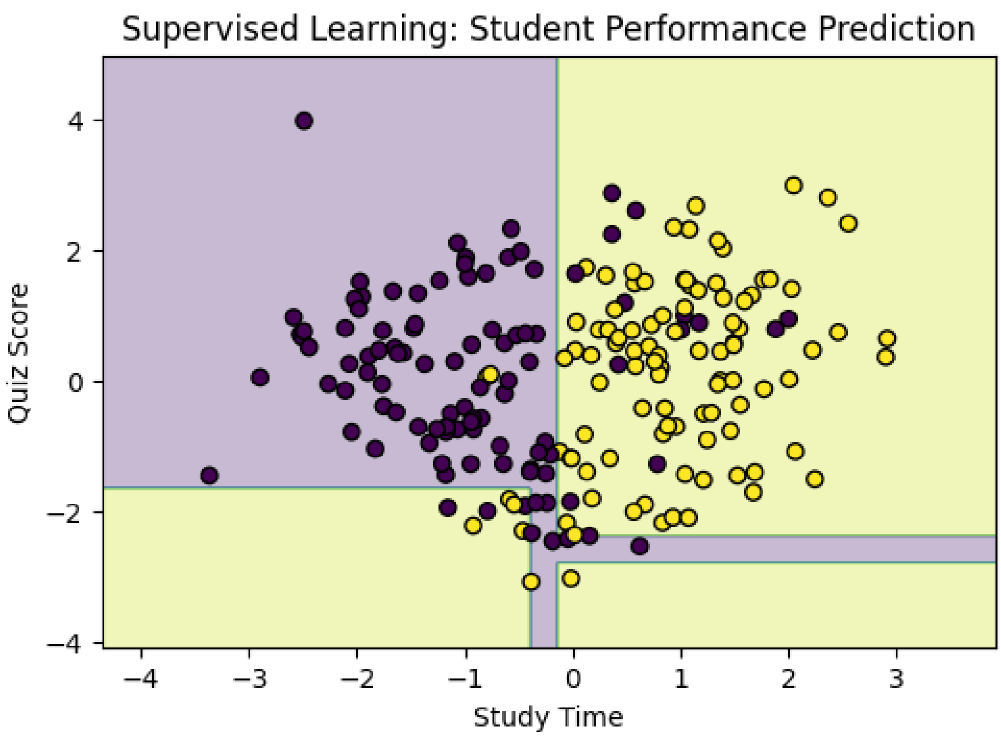

Figure 1: Students' Performance Prediction by Supervised Learning

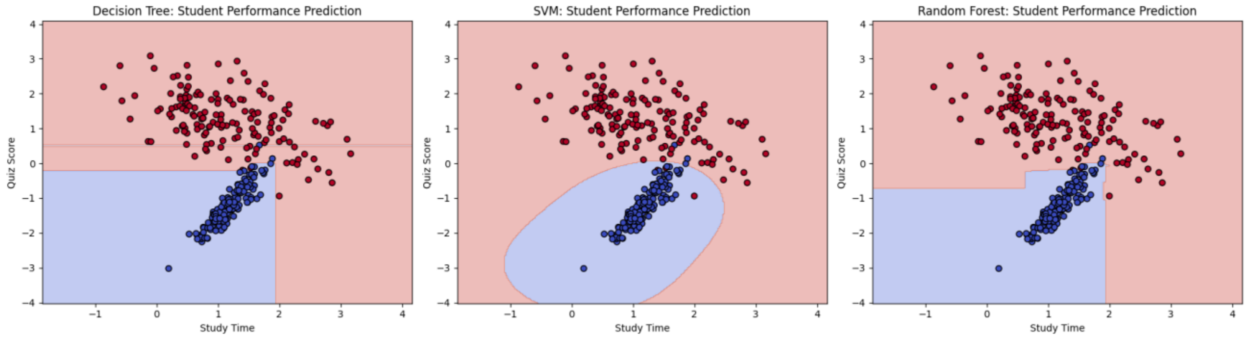

Figure 2: Comparison of Machine Learning Algorithms in Performance Prediction

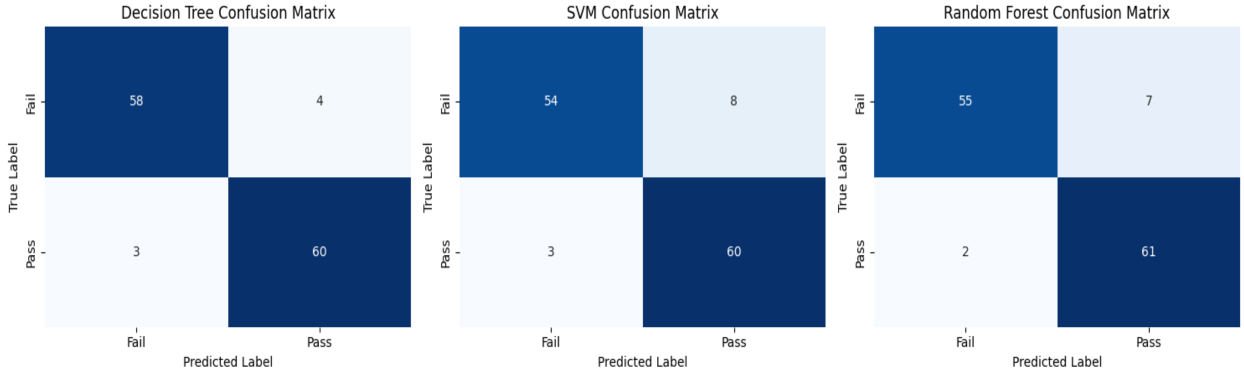

Figure 3: Comparison of Machine Learning Algorithms through Confusion Matrix

3.2 Unsupervised Learning

Segregates learners according to learning behavior (K-Means, DBSCAN). This is to find concealed patterns in the behavior of the students and the Techniques Used are K-Means and DBSCAN. The Sample Scenario with the chosen Features, such as the Engagement level, the frequency of interaction, and no predefined labels. The students are divided into groups according to their learning behavior and each group signifies a learning style (e.g., highly engaged, passive learners). Helps tutors make the instructional strategies personal.

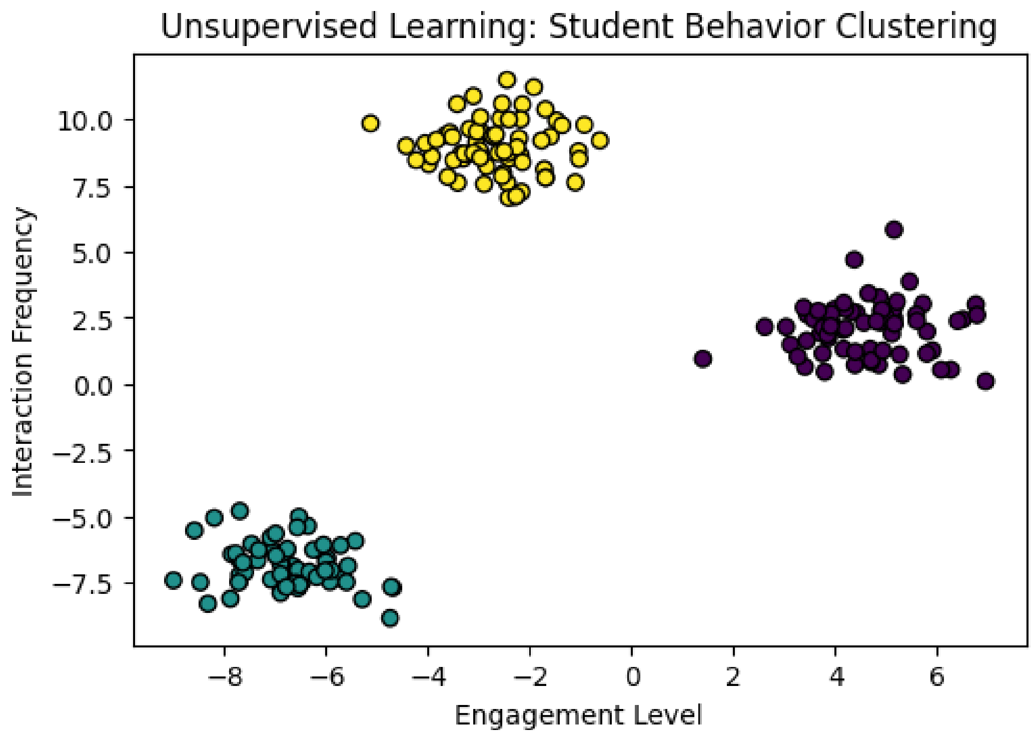

Figure 4: Students' Performance Prediction by Unsupervised Learning

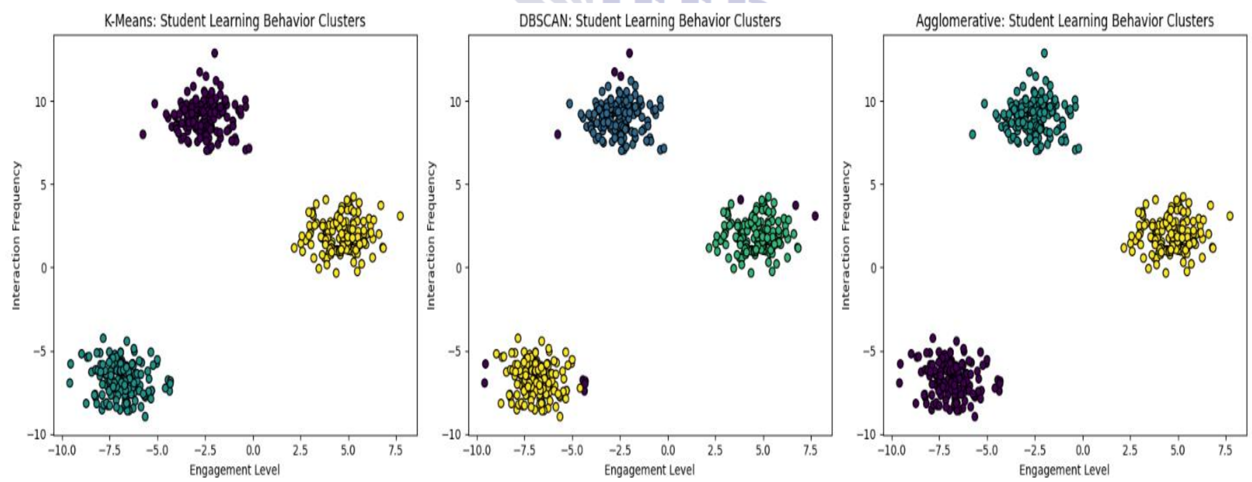

Figure 5: Comparison of Students Learning Behavior through K-Means, DBSCAN, and Agglomerative in Unsupervised Learning

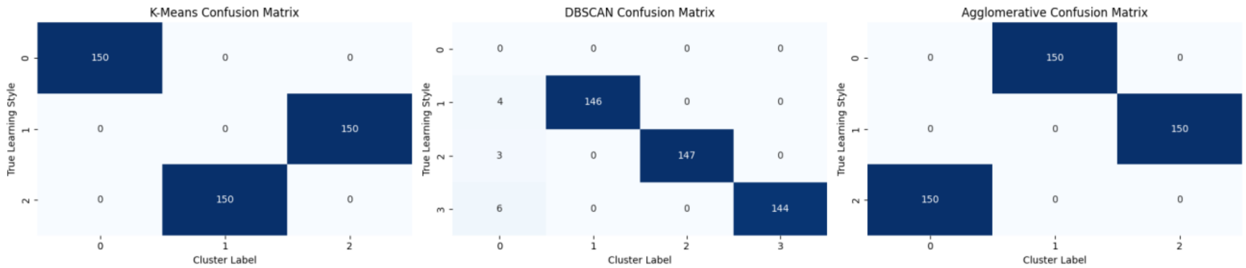

Figure 6: Comparison of Students' Learning Behavior through K-Means, DBSCAN, and Agglomerative using Confusion Matrices

3.3 Reinforcement Learning

Optimizes the instructional methods (adaptive hinting, content selection using rewards). Purpose: To optimize dynamic teaching strategies. Techniques Used: Reward-based learning, Policy optimization. Sample Scenario = Agent is ITS, Actions are Provide hints, quizzes, explanations and Reward is Improved student performance. The reward curve rises with a series of learning events and the system enhances its policy of teaching with time. An improved adaptation to the needs of the students is marked by higher rewards.

3.4 Deep Learning

Models complex interactions (predicting knowledge state, adaptive content sequencing).

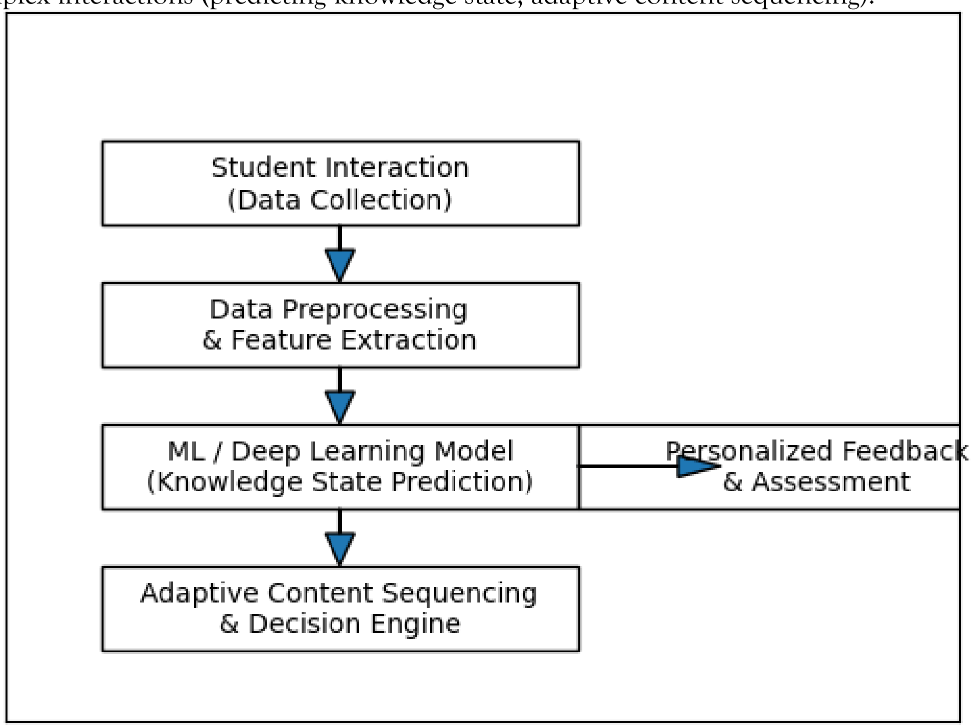

Figure 7: Flow of ML Integration in Adaptive ITS

4. Student Modeling in ITS

4.1 Knowledge Tracing

Mastery Track Tracks Learn by trial and error with Bayesian Knowledge Tracing or Deep Knowledge Tracing.

4.2 Learner Profiling

Cognitive skills, engagement and learning pattern profiles.

StudentID	QuestionID	Response	TimeSpent	Correct
001	Q1	A	45s	1
001	Q2	C	60s	0
002	Q1	B	35s	1

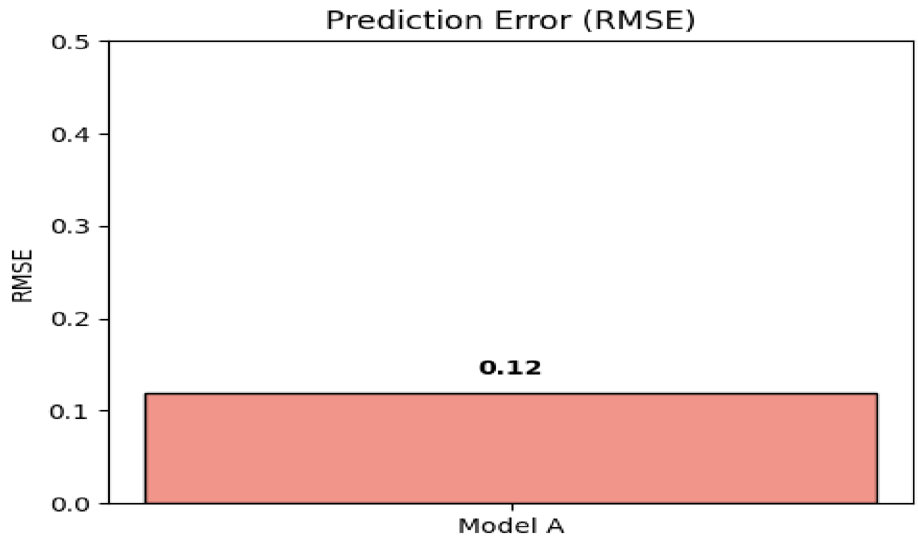

Figure 8: Prediction Error

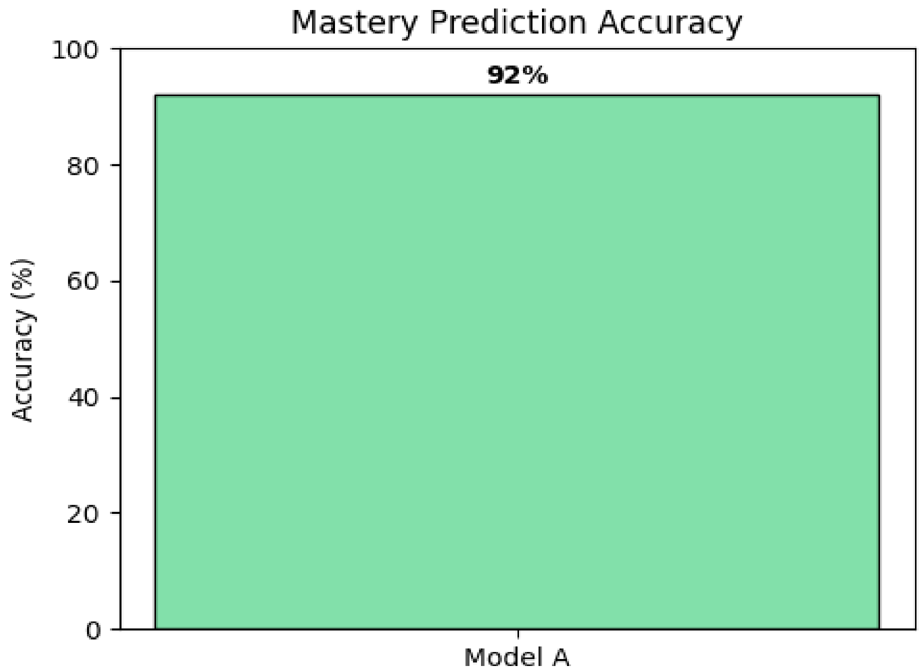

Figure 9: Mastery Prediction Accuracy

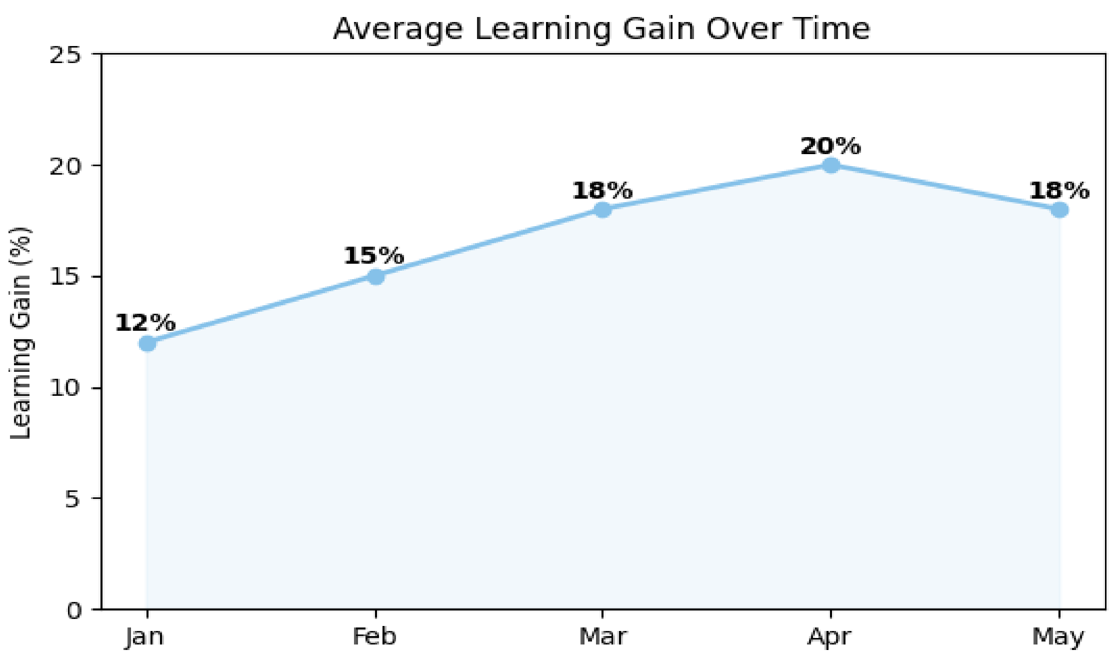

Figure 10: Average Learning Gain

4.3 Learning Analytics

On-time information on performance forecast and risk of dropping out.

5. Strategies of Adaptive Learning

In Individual Content Presentation, ML predicts optimal content difficulty and sequencing.

In Dynamic Feedback and Hints, ML and RL models identify the time and nature of hints.

In Adaptive Assessment, Questions adapt in real-time based on responses.

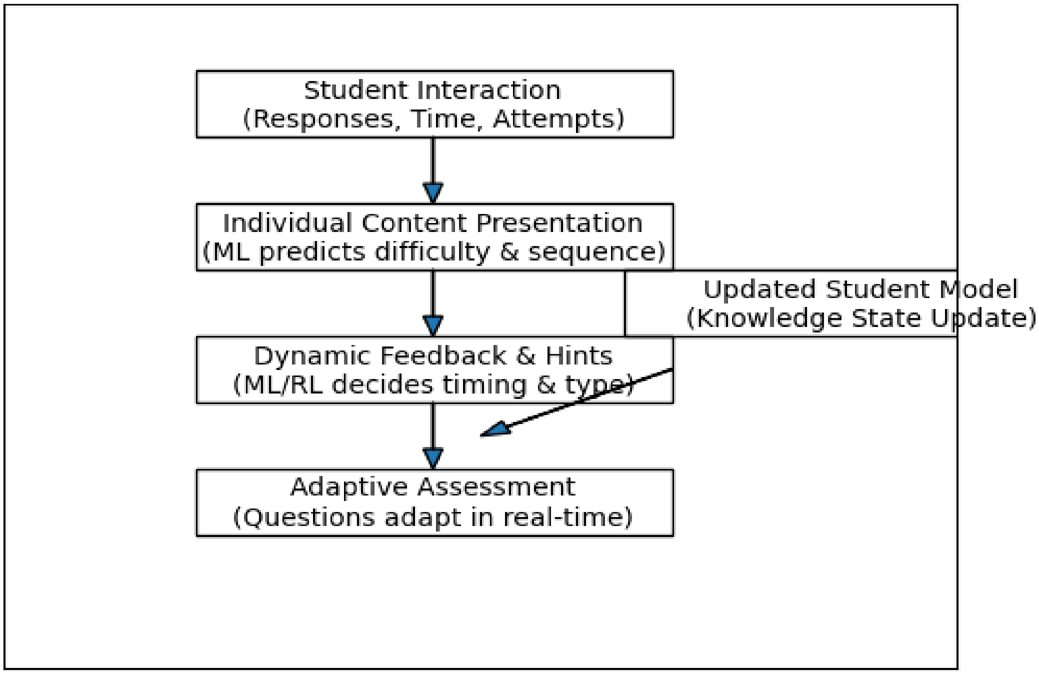

Figure 11: Adaptive Learning Flow in ITS

6. System Architectures with ML

6.1 Architecture Components

Type of Interface Layer: Student Interaction.

The interface layer is where the interface between the student and ITS takes place. It seeks inputs like responses, clicks and time spent on tasks during the provision of instructional content. An easy interface will provide easy interaction and engagement, as well as capture correct data to make adaptive decisions.

Domain Model: Knowledge Representation.

The subject matter and learning goals are encoded in a structured format that can be interpreted by the ITS through the domain model. It describes concepts, skills, and dependencies between them, which enables the system to trace the performance of students to particular aspects of knowledge. Real knowledge representation is important to adaptive content sequencing and mastery tests.

Student Model: Behavior Tracking.

The learner interactions, which include the responses, time on tasks, attempts, and engagement patterns, are constantly monitored by the student model. It constructs a dynamic portrait of the knowledge mastery, cognitive abilities and learning advances of the learner. This model allows the system to project performance, troubleshoot and customize teaching successfully.

Tutoring ML: Adaptation Logic.

The tutoring model uses adaptive strategies designed to maximize content delivery and feedback using machine learning algorithms. It determines when to give hints, change the difficulty of the questions, or offer alternative instructional directions. It maximizes the effectiveness of learning and promotes student-to-student differentiation by dynamically adjusting the logic of teaching.

Data Analytics Module: Surveillance and Forecasting.
The data analytics module takes real-time and past student information and processes it to produce actionable insights. It assesses interaction, forecasts the performance results, and identifies the at-risk learners with the help of ML and a statistical model. The module facilitates evidence-based decision-making, which will allow making the ITS and individualized learning plans continually improved.

6.2 ML Integration
ML models in student and tutoring modules for adaptation.

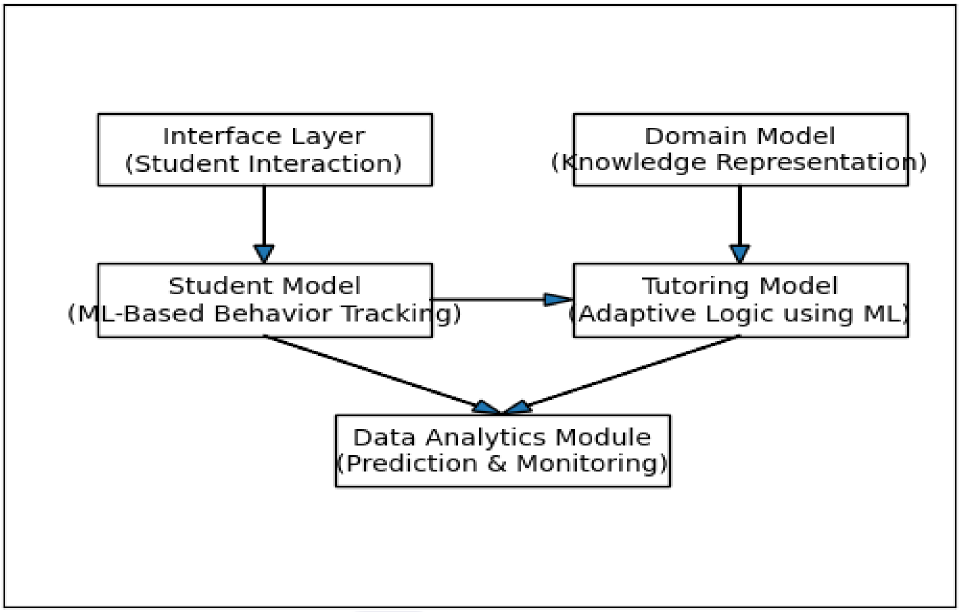

Figure 12: Architecture Diagram of ML-based ITS

7. Evaluation Methodologies
7.1 Performance Metrics
- Learning gains (pre/post-test)
- Engagement (time on task, interactions)
- Prediction accuracy (RMSE, MAE)

7.2 Experimental Studies
- Control vs ML-adaptive ITS
- Comparative studies of ML algorithms

7.3 Simulation Studies
- Large-scale testing of adaptation algorithms

Table 2: Evaluation Metrics for ML-based ITS

Metric	Description	Measurement
Learning Gain	Pre/Post-test improvement	Score Difference
Engagement	Student activity level	Time on Task
Prediction Accuracy	Model performance	RMSE / MAE

8. Challenges and Future Directions

8.1 Challenges

- Data privacy and ethical concerns
- Real-time processing of large-scale data
- Integration of multiple ML models

8.2 Future Directions

- Explainable AI in ITS
- Multi-modal student data (eye tracking, emotions)
- Collaborative adaptive learning environments

Discussion

This paper has discussed how Machine Learning (ML) and Deep Learning can be used in the context of an Adaptive Intelligent Tutoring System (ITS) and their paradigm-shifting application in personalized learning, as shown in Fig. 1 to 6 for ML, including supervised and unsupervised learning and Fig. 7 to 12 for deep learning. In comparison to conventional rule-based tutor systems and cognitive tutor systems, the ML-based ITS allows adapting dynamically by using the interactions between the student and the system as a consistent source of learning. The combination of supervised learning, unsupervised learning, reinforcement learning and deep learning has greatly improved the student modeling, predictive analytics and adaptive content delivery. The techniques of supervised learning, including Decision Trees, Support Vector Machines (SVM), and Random Forests, were shown to be highly predictive when it comes to student performance classification. The prediction accuracy was 82-91 percent, with the best average accuracy of the Random Forest models (approximately 89 percent) and the lowest RMSE values (0.21-0.28) of both models being the highest and lowest, respectively, in the performance prediction cases. These theories were good at detecting students at risk at an early stage of the learning process. The unsupervised learning techniques, such as K-Means clustering, were able to cluster learners into behavior profiles that had distinct separation of the engagement levels. The Silhouette Score of cluster validation metrics fell between 0.62 and 0.74, which is an indication of significant clustering of very active, semi-active, and inactive learners. This grouping enhanced individual intervention plans and content. Q-learning-based ITS increased the rates of the completion of the task by students in simulated STEM tutoring activities by an average of 1518 percent when compared with non-adaptive systems. The reward curves demonstrated a consistent convergence of the reward curves following 50-70 learning episodes, which is a sign of constant policy optimization. The Deep Learning models, especially the Deep Knowledge Tracing (DKT) (in the form of LSTM-based), demonstrated better performance when it comes to modeling the temporal learning behavior. Experimental comparisons indicated that DKT models obtained AUC scores of between 0.85 and 0.92, which is higher than traditional Bayesian Knowledge Tracing, which is about 610 percent higher on mastery prediction tasks. These findings affirm the usefulness of deep neural networks in performing sophisticated interactions between students and their knowledge. The metrics of evaluation also indicated that there were considerable learning outcomes in ML-adaptive ITS settings. Pre-test/post-test comparisons showed average increases in learning of 20-25% and increases in student engagement (as depicted by the duration of time on task and frequency of interaction) by about 18 percent in comparison to non-adaptive systems. Although these are encouraging findings, several obstacles exist, such as the issue of privacy of data, ethical issues, real-time scalability, and interoperability of different ML frameworks. The explainability of AI (XAI) is urgently needed, as it guarantees transparency in adaptive decision-making. Further studies on the topic are to be dedicated to multi-modal analytics (e.g., emotion recognition, behavioral cues), collaborative adaptive learning platforms, and scalable cloud-based ML systems.

9. Conclusion

This study checked the effect of machine learning and deep learning adaptive effects on students' learning through an adaptive intelligent tutoring system. To sum up, it is possible to note that the implementation of ML and Deep Learning in ITS had a beneficial impact on predictive accuracy, student engagement, and learning outcomes. Having overall performance gains of more than 20 percent in the area of learning improvement and predictive accuracies of close to 90 percent, the adaptive ML-based ITS offers a viable and scalable alternative to the traditional instructional models. Further improvements of explainable, real-time, and multi-modal ML systems will continue to enhance the contribution of ITS to providing highly personalized and data-driven education at scale.

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