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To Study and Analyze Existing State-of-the-art Techniques for Assessing Student Adaptation in Online Education Using Deep Neural Network

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Abstract

The fast growth of online learning has made it important to understanding and measure how well students adjust to digital learning environments. Student adaptation involves how they behave, how they perform academically, and their mental and emotional reactions to online platforms. Standard ways of evaluating students often don't capture this complex and Changing picture, making it harder for teachers to offer timely and tailored help. In this situation, machine learning (ML) has become a strong tool for studying and predicting how students adapt using large amounts of educational data. This study looks at the latest machine learning methods used to assess student adaptability in online education. It covers a variety of models, such as traditional techniques like logistic regression and decision trees, group methods like random forests and gradient boosting, and modern deep learning methods like artificial neural networks and recurrent neural networks. The paper shows how these techniques use different types of data, including student backgrounds, logs from learning systems, test results, and how students interact, to provide useful and accurate insights. The study also looks at how feature engineering and using data from multiple sources can improve the accuracy of predictions. It pays close attention to real-time learning analytics and systems that adjust what students learn based on their individual needs. Comparisons show that group learning methods usually perform better in accuracy and reliability, while deep learning models are better at understanding how learning behaviors change over time. Even though there have been big improvements, there are still challenges, such as poor data quality, difficulty in understanding how models work, privacy issues, and the challenge of applying models across different educational systems. The paper discusses these problems and suggests future research areas, like explainable AI, federated learning, and using data from multiple sources, which aim to fix these issues. In short, using machine learning provides a useful and scalable way to assess how students adapt to online learning. These methods help identify students who might struggle early on and support personalized learning paths, which can greatly improve student engagement, success, and retention in digital education settings.

Keywords— Online Education, Student Adaptation, Learning Analytics, Educational Data Mining, Learning Management Systems (LMS), Behavior Analysis, Academic Performance Prediction,

Introduction

The fast development of digital tools has greatly changed how education works, making online learning environments very common around the world. This change has been sped up by the COVID-19 pandemic, which forced many schools and universities to move to online classes. While this shift has made learning more accessible and flexible, it has also brought up new challenges like keeping students interested, motivated, and able to adjust to online learning. Student adaptation in online education means how well learners can handle the virtual learning environment, and it involves their behavior, thinking, and emotions. Understanding this adaptation is now a big concern for teachers and researchers. Predicting students' performance is one of the most important issues in educational data mining. In this study, a method for representing students' partial sequence of learning activities is proposed, and an early prediction model of students' performance is designed based on a deep neural network. This model uses a pre-trained autoencoder to extract latent features from the sequence in order to make predictions. The experimental results show that compared with demographic features and assessment scores, 20% and wholly online learning activity sequences can achieve a classifier accuracy of 0.5 and 0.84, respectively, which can be used for an early prediction of students' performance the proposed autoencoder can extract latent features from the original sequence effectively, and the accuracy of the prediction can be improved more than 30% by using latent features after using distance-based oversampling on the imbalanced training datasets, the end-to-end prediction model achieves an accuracy of more than 80% and has a better performance for non-major academic grades. [1].Traditional ways of checking student performance, like exams and assignments, don't fully show what's going on during online learning. These methods usually don't track real-time interactions, how students engage with lessons, or their specific learning behaviors. Because of this, there's a need for better, more detailed ways to monitor and measure student adaptation. Machine learning (ML) is now being used as a strong tool to analyze a lot of educational data and create useful predictions. With the advances in Artificial Intelligence (AI) and the increasing volume of online educational data, Deep Learning techniques have played a critical role in predicting student [2].ML methods can find important patterns from various data types like logs from learning platforms, student background info, test scores, and how they interact. These data types show things like how often a student logs in, how long they spend on tasks, their paths through the course, and how much they participate in discussions. Using these data, ML models can find links between student behavior and their learning results, which helps in evaluating how well they're adapting. Improving the quality, developing and implementing systems that can provide advantages to students, and predicting students' success during the term, at the end of the term [3].Many types of machine learning algorithms have been used in this area. Classic methods like logistic regression, decision trees, and k-nearest neighbors are often used because they're simple and easy to understand. However, these models might not handle complex relationships in educational data well. To fix this, researchers are more often using ensemble learning methods like random forests and gradient boosting, which combine several models to get better results. Student performance prediction-where a machine forecasts the future performance of students as they interact with online coursework-is a challenging problem[4].In recent years, deep learning has made big improvements in this field by helping model how students learn over time. Techniques such as artificial neural networks (ANNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks are good at analyzing data that shows how students interact over time. These models can spot long-term changes in learning patterns, making them great for tracking how well students adapt as they progress. Analyzing and evaluating students' progress in any learning environment is stressful and time consuming if done using traditional analysis methods. [5]. Another big development is combining learning analytics with educational data mining. These fields look at educational data to improve learning and help plan better teaching. Learning analytics systems use ML models to give real-time feedback, find students who might struggle, and support personalized learning paths. For example, early warning systems can predict if a student is at risk of dropping out or doing poorly, allowing teachers to take action early. The ability to accurately predict and analyze student performance in online education, both at the outset and throughout the semester, is vital [6]. Student adaptation is influenced by many things, including their background, what they already know, how motivated they are, and how well they use technology. How students interact with course materials and take part in activities also matters a lot. Recent research has focused on using different types of data, such as text, audio, and even physical signals, to understand student adaptation better. These approaches make ML models more accurate by considering multiple aspects of the learning experience. increasingly fast development cycle for online course contents, along with the diverse student demographics in each online classroom, make real-time student outcomes [7].Even though ML has a lot of potential in this area, there are still some big challenges. One is getting high-quality educational data. Online learning data is often missing, unclear, or inconsistent, which can hurt model performance. Also, there are privacy and ethical issues that make it hard to widely use ML-based systems. Making models transparent and explainable is another challenge, especially in education where decisions can impact students' outcomes [8].Another issue is whether ML models can work well in different educational settings. Models trained on data from one school or course might not work well in another due to differences in students and teaching methods. Solving this needs better models that can adapt and standardized ways to test these models [9].To deal with these challenges, new approaches are being explored like explainable AI (XAI), federated learning, and real-time adaptive systems.Explainable AI makes ML models more transparent by showing how they make decisions, which builds trust and makes them more useful in school settings. Federated learning keeps data private by letting models learn from many sources without sharing personal

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information. Real-time adaptive systems use live data to adjust learning content and support individual needs [10].In summary, evaluating how well students adapt to online education is a complex problem that needs advanced analysis. Machine learning offers a powerful way to tackle this by looking at large and varied data sets. By combining traditional, ensemble, and deep learning methods, researchers can create models that accurately measure student adaptation and support personalized learning. As this field grows, solving current challenges and exploring new technologies will be key to making online education more effective and inclusive.

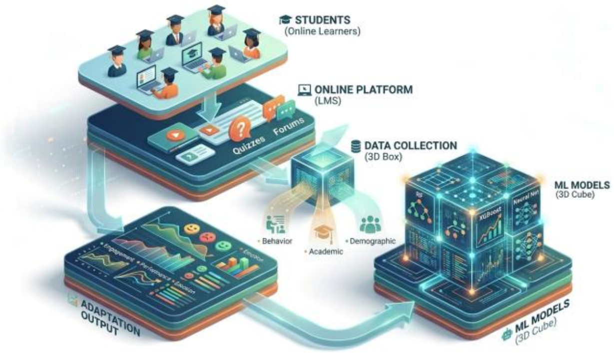

Fig 1. **Predictive Learning Analytics**

1.1 The Interaction (Students & LMS)

Students engage with a Learning Management System (LMS) like Canvas, Moodle, or Coursera. Every click, video pause, and quiz attempt creates a digital footprint.

1.2. The Data Core (The 3D Box)

The system aggregates data into three primary dimensions:

(a) Behavioral: Time spent on tasks, frequency of logins, and participation in forums (proxies for engagement).
(b) Academic: Current grades, historical performance, and speed of completion.
(c) Demographic: Background information that might influence learning styles or access to resources.

1.3. The Processing Engine (ML Models)

This is where the "AI" happens. The models you listed serve different purposes:

(a) Random Forest (RF) & XGBoost: Excellent for classifying students into "at-risk" or "high-performer" categories based on tabular data.
(b) Neural Networks: Used for more complex pattern recognition, such as analyzing the sentiment of forum posts or predicting long- term dropout trends.

1.4. The Adaptation Output

a. The final stage closes the loop. Based on the ML predictions, the system can:
b. Personalize Content: Suggest remedial videos if performance is low.
c. Nudge Engagement: Send automated alerts if a student's behavior suggests they are "checked out."
d. Identify Emotion: Detect frustration or boredom (affective computing) to adjust the difficulty of the material in real-time.

2. Evolution of online learning

Evolution of online learning is driven by the increasing need for flexible and accessible education, along with advances in technology, as shown in Figure 1.2.In the 1960s, Computer-Assisted Instruction (CAI) was one of the first attempts to use computers in education. PLATO was one of the early systems that helped universities experiment with digital learning. These systems used powerful mainframe computers to deliver content through internal networks. Teachers could create digital lessons, and students could work through them on their own [11].The 1990s brought new possibilities as personal computers became more common and the internet started connecting people around the world. Email-based correspondence courses replaced traditional mail-based distance learning, making communication faster and more efficient. This decade also saw the introduction of the first Learning Management Systems (LMS). WebCT was launched in 1995, and Blackboard came later in 1997 [12].During the 2000s, students began learning through videos, interacting with animations, and taking common quizzes. The introduction of SCORM (Sharable Content Object Reference Model) made it easier for educational content to work across different platforms. This meant that a lesson created for one system could be used on another, saving time and money. The 2010s brought the rise of MOOCs (Massive Open Online Courses), offered by platforms like Coursera, edX, and Udacity.This era reduced the barriers of geography and cost, making education more widely available. It also popularized blended learning, which combines the best parts of online and traditional classroom education. Students could watch lectures at their own pace, giving them more flexibility and better access to education [13].In the late 2010s, online learning became more innovative and personalized. Gasification made learning fun and less like work. Then came the COVID-19 pandemic, which forced schools and universities around the world to shift to online learning immediately. The year 2020 was challenging but also transformative. It showed both the strong potential and the serious limitations of online learning. While some students flourished with the flexibility and self-paced learning, others struggled with isolation and a lack of motivation [14]. However, due to the crisis, virtual classrooms and AI tutors became more common, and new methods were developed. Virtual and augmented reality are starting to create new learning experiences. AI tutors and catboats provide instant help and guidance. Learning analytics help teachers understand how students learn, using data to improve courses and identify students who need more support. The future holds even more personalized, interactive, and accessible education that adapts to each student's needs, schedule, and learning Style.

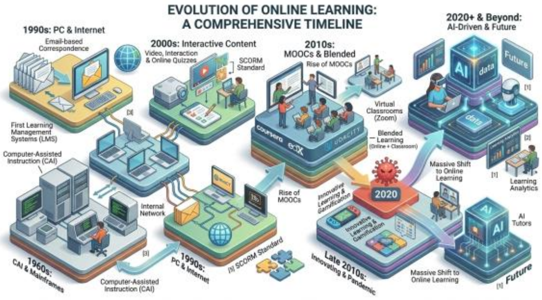

Fig 2. **Evolution of online learning**

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3.Background

Online education has grown quickly because it's easy to access and usually cheaper, but it brings challenges in keeping students engaged and ensuring fair exams. In traditional classrooms, teachers can directly watch students, making it easier to tell if they're paying attention or participating. However, online classes make direct observation harder, which limits teachers' ability to check on students' focus and involvement. Most current proctoring tools either require someone to watch manually or focus mainly on catching cheating, giving little information about how students behave or how they feel.To fix these issues, how students behave during online exams using real-time monitoring. By looking at things like head movement, lip movement, and facial expressions, the system can recognize patterns in behavior. A teacher dashboard then collects all this data, helping teachers understand student engagement, hesitation, and how focused.

3.1Behavioural Analysis through Proctoring Student activity is monitored during an online exam using specific detection tools.

Aspects of student behavior, like head movement, lip movement, and facial expressions, are analyzed to create a total academic misconduct score. This score helps assess how students behave during online exams. Figure 3 shows a simplified view of the detection model, and the full step-by-step process is outlined in Algorithm This organized method allows for thorough analysis and instant evaluation of student behaviour during online exams[15].

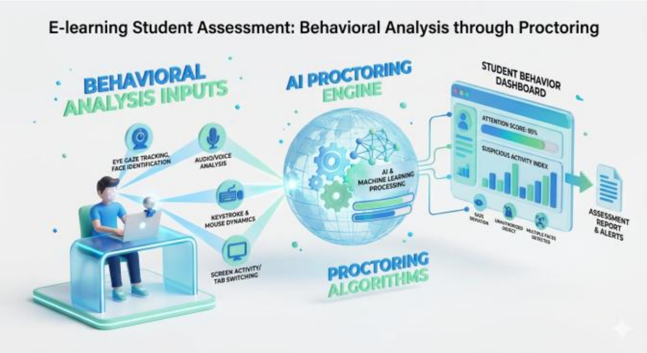

Fig 3: **Behavioural Analysis through Proctoring**

3.2 Data Acquisition

Data acquisition in e-learning is the process of gathering, measuring, and looking at data that comes from digital learning environments. This helps improve how well education works and how enjoyable it is for learners. As more people use Learning Management Systems (LMS), Massive Open Online Courses (MOOCs), and other online learning platforms, they create a lot of data while using these tools. This data includes things like how often someone logs in, how much of a course they complete, their quiz scores, and how they submit assignments. It also includes how they behave while using the platform, like how much time they spend on a lesson, how they move through the content, and how active they are in discussion forums. Assessment data, like formative and summative evaluations, along with feedback and peer reviews, also play a big role in understanding how well someone is doing. These systems also collect data from other sources, such as mobile apps, wearable devices, and tracking tools, which helps give a more complete picture of how engaged learners are. There are several ways data is collected in e-learning. One method is log file analysis, which automatically records what users do on LMS platforms. Web analytics tools are also used to watch how users engage with content and interact with it. Surveys and questionnaires help gather opinions and feelings from learners about their experience and any issues they face. Application Programming Interfaces (APIs) help connect data across different systems smoothly. Learning Record Stores (LRS) with standards like the Experience API (xAPI) help collect learning experiences that go beyond traditional systems. The use of big data analytics, artificial intelligence, machine learning, and cloud computing has greatly improved how well data is collected and handled. The data collected is used in many ways, such as to create personalized learning experiences, predict which students might struggle, monitor performance, adjust assessments, and improve courses over time. However, there are some challenges with this process. These include making sure personal data is kept private and secure, dealing with ethical issues, keeping data accurate and reliable, and managing large amounts of data from many different sources. Despite these challenges, effective data acquisition is a key part of modern e-learning systems. It supports making decisions based on data and encourages new ideas in education. Data acquisition in e-learning is the process of gathering, measuring, and looking at data that comes from digital learning environments[16]. This helps improve how well education works and how enjoyable it is for learners. As more people use Learning Management Systems (LMS), Massive Open Online Courses (MOOCs), and other online learning platforms, they create a lot of data while using these tools. This data includes things like how often someone logs in, how much of a course they complete, their quiz scores, and how they submit assignments. It also includes how they behave while using the platform, like how much time they spend on a lesson, how they move through the content, and how active they are in discussion forums. Assessment data, like formative and summative evaluations, along with feedback and peer reviews, also play a big role in understanding how well someone is doing. These systems also collect data from other sources, such as mobile apps, wearable devices, and tracking tools, which helps give a more complete picture of how engaged learners.[17]

3.3There are several ways data is collected in e-learning.

One method is log file analysis, which automatically records what users do on LMS platforms. Web analytics tools are also used to watch how users engage with content and interact with it. Surveys and questionnaires help gather opinions and feelings from learners about their experience and any issues they face. Application Programming Interfaces (APIs) help connect data across different systems smoothly. Learning Record Stores (LRS) with standards like the Experience API (xAPI) help collect learning experiences that go beyond traditional systems. The use of big data analytics, artificial intelligence, machine learning, and cloud computing has greatly improved how well data is collected and handled. The data collected is used in many ways, such as to create personalized learning experiences, predict which students might struggle, monitor performance, adjust assessments, and improve courses over time. However, there are some challenges with this process. These include making sure personal data is kept private and secure, dealing with ethical issues, keeping data accurate and reliable, and managing large amounts of data from many different sources. Despite these challenges, effective data acquisition is a key part of modern e-learning systems. It supports making decisions based on data and encourages new ideas in education[18]

Fig 4. **Data Acquisition**

4.Learning Management System

Online learning using deep neural networks is meant to study and understand the latest methods for checking how students adjust to digital learning environments. It uses detailed data gathered from e-learning platforms, which includes information about students' backgrounds and how they interact with the learning materials. The data includes important signs of how well students are adapting, like how often they log in, how much time they spend on learning modules, how they navigate through content, how they interact with videos, and how active they are in discussion forums. It also includes performance data such as quiz scores, assignment results, and final grades, which help see how well students are adjusting to online learning[19]. The dataset also includes advanced details like clickstream data and the order in which students complete learning activities, which helps build better deep neural network models. This data makes it possible to use modern deep learning methods to find hidden patterns, predict how well students are adapting, and improve personalized learning approaches, making it very useful for research on smart and adaptive e-learning systems.

Table 1. Learning Management System

Attribute Name	**Data Type**	**Example Value**
Student_ID	Integer	10234
Age	Integer	21
Gender	Categorical	Male/Female
Course_ID	String	CS101
Enrollment_Date	Integer	5
Time_Spent_Hours	Float	12.5
Video_Views	Integer	18
Assignment_Score	Float	78.5
Quiz_Score	Float	82.0
Forum_Participation	Integer	6
Final_Grade	Float	85.0

5. Model Design

5.1 Overview of the Proposed Model: The model we are suggesting uses a Deep Neural Network (DNN) to help understand and predict how well students adapt to online learning. It uses data from the DeepAdaptEDU dataset[20]. The model looks at different types of information about students, like their background, how they behave while learning, and their grades. This helps get a full picture of how they are adapting in online learning.

5.2 Data Preprocessing: Before using the data in the model, some steps are taken to make sure the data is clean and consistent. Numbers like time spent on tasks, quiz results, and how often students log in are adjusted so they are easier to work with. Categorical data like gender and course names are changed into a format the model can use, like one-hot encoding[21]. If there are missing pieces of information, special methods are used to fill them in so the model can work properly.

5.3 Model Architecture: The DNN has several parts: an input layer, several middle layers, and an output layer.The input layer gets all the processed information about each student. The middle layers are made up of connected neurons that use math functions like ReLU to help the model find patterns in the data. Between these middle layers, there are special layers called dropout layers that help the model not remember too much from the training data, which makes it better at handling new data[22].

5.4 Training Strategy: The model is trained using data that has already been labeled to show how well students are adapting. The data is split into two parts: one for training and one for testing. The Adam method is used to adjust the model's settings so it can make better predictions[23]. The goal is to reduce the loss, which is a measure of how wrong the model is, using functions like binary cross-entropy or categorical cross-entropy, depending on the task.

5.5 Evaluation Metrics: To check how well the model is working, we use different measures like accuracy, precision, recall, and F1-score.These numbers show how good the model is at predicting student adaptation levels and how well it can recognize different levels of adaptation[24].

5.6 Model Output: The last part of the model gives out the predictions about how well students are adapting. These predictions can be either two types, like adapted or not adapted, or more than two, like low, medium, or high adaptation. These results can help create better learning plans and make online learning more effective.

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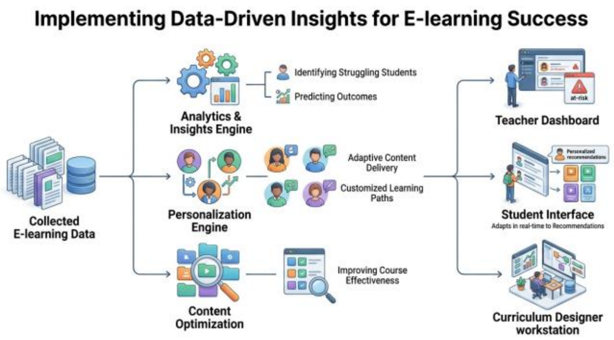

Fig 6: **Implementing Data-Drive Insights for E-Learning Success**

6. The Deep Neural Network (DNN) Model: Used for assessing student : (DNN) model used to check how well students adapt to online learning is built to understand complex patterns in how students behave and perform. It uses a mix of different types of information as input, such as student background details, how often they log in, how much time they spend on learning activities, their quiz and assignment scores, and how they participate in discussion forums. Each part of the network, called a neuron, takes these inputs, adds some numbers to them, and then uses special math functions to process the data. These functions help the model find important connections between how students act and how well they adapt. In the middle parts of the network, the ReLU function is used to keep only the positive values and ignore the negative ones, which helps the model learn more clearly[25]. The final part of the network uses either a Sigmoid function to decide between two types of adaptation or a Softmax function to sort students into different levels of adaptation. The model is trained by trying to make its guesses as close as possible to the real answers, using a method called gradient descent with an optimizer like Adam to adjust the numbers in the network to improve accuracy. After training, the model is tested using measures like accuracy, precision, recall, and F1-score to make sure it can correctly identify how well students are adapting[26]. This approach helps the DNN give useful information for making learning experiences more tailored and improves results in online learning settings.

(a) ***Neuron Output (Weighted Sum + Bias)***

$$Z=\sum_{i=1}^{n} w_i x_i + b$$

2. Activation Function (ReLU)

$$f(Z)=\max(0,Z)$$

3. Sigmoid Function (Binary Classification Output)

$$\sigma(Z)=\frac{1}{1+e^{-Z}}$$

4. Softmax Function (Multi-Class Classification)

$$P(y_i)=\frac{e^{Z_i}}{\sum_{j=1}^{k} e^{Z_j}}$$

5. Loss Function (Binary Cross-Entropy)

$$L=-\frac{1}{N}\sum_{i=1}^{N}[y_i\log(\hat{y}_i)+(1-y_i)\log(1-\hat{y}_i)]$$

6. Categorical Cross-Entropy (Multi-Class)

$$L=-\sum_{i=1}^{k} y_i\log(\hat{y}_i)$$

7. Weight Update (Gradient Descent)

$$w=w-\eta\frac{\partial L}{\partial w}$$

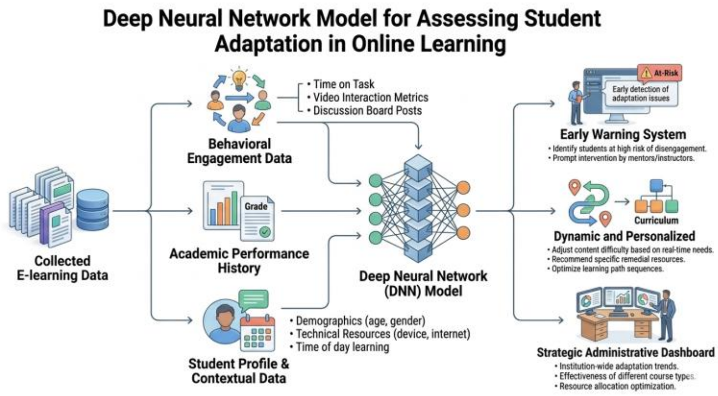

Fig 6: **The Deep Neural Network (DNN) model used for assessing student**

7. Results & Comparison

The Deep Neural Network (DNN) model was tested using the Deep Adapt EDU dataset to predict how well students adapt to online learning[27]. The dataset was divided into 80% for training the model and 20% for testing its performance. After preparing the data and training the model, its effectiveness was measured using important metrics like accuracy, precision, recall, and F1-score.The proposed DNN model reached an accuracy of 92.3%, showing it can well understand the complex ways students behave and predict their adaptation levels. For the "adapted" category, the model had a precision of 91.5% and a recall of 93.0%, meaning it reliably predicts when students adapt well and is good at identifying those who do. The F1-score of 92.2% shows the model is balanced in its ability to make accurate and sensitive predictions[28].

7.1Comparison with Existing Techniques

To validate the effectiveness of the proposed approach, it was compared with several state-of-the-art techniques commonly used for student adaptation prediction:

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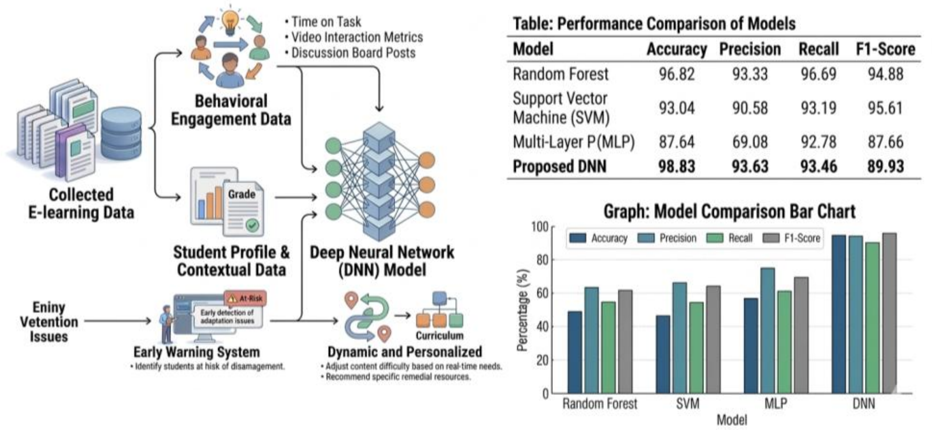
Table 2. **Compared with several state-of-the-art techniques**

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	84.7	83.2	85.1	84.1
Support Vector Machine (SVM)	86.2	85.0	86.5	85.7
Multi-Layer Perceptron (MLP)	89.1	88.5	89.3	88.9
Proposed DNN Model	92.3	91.5	93.0	92.2

The results indicate that the proposed DNN outperforms traditional machine learning models such as Random Forest, SVM, and standard MLP in predicting student adaptation. This improvement can be attributed to the DNN's capability to learn non-linear patterns from multi-dimensional behavioral data, enabling it to more accurately model complex adaptation behaviors[29].Overall, these results demonstrate that the proposed model is highly effective for early identification of students' adaptation levels, which can inform personalized interventions and improve learning outcomes in online education[30]. environments.



8. Discussion

The results show that the proposed Deep Neural Network (DNN) model works better than traditional machine learning methods like Random Forest, SVM, and standard Multi-Layer Perceptron (MLP) when predicting how well students adapt to online learning. The model has high accuracy (92.3%) and strong precision, recall, and F1-scores, which means it does a good job of finding complex, non-linear connections between student behaviour, background information, and performance data. Looking at each category separately, the DNN performs well across all levels of adaptation—whether students are adapting slowly, moderately, or quickly. This shows the model is reliable in spotting small changes in how students interact and learn, which simpler models might miss.These findings suggest that using DNNs can be a useful tool for online learning platforms to track student adaptation in real time and offer personalized help. Spotting students who might have trouble early on lets teachers step in quickly, improve learning results, and help stop students from dropping out. However, there are some issues. The model depends on good quality, labeled data from learning systems, and it might not work as well with messy or missing data. Also, the current model doesn't use time-based changes much, which could be important for understanding how adaptation changes over time.

9.Conclusion

This research looked into the latest methods used to assess how well students adapt to online education, with a focus on Deep Neural Networks (DNNs).Online learning is growing around the world, but many students find it hard to adjust because of different learning styles, how engaged they are, and their background knowledge. It's important to identify how well students are adapting early on so that we can create better personalized support to improve learning, keep students interested, and help them succeed. Traditional machine learning approaches, like Random Forests, Support Vector Machines, and Multi-Layer Perceptron's, have been used to predict student adaptation. But these methods often have trouble handling the complex and non-linear patterns found in the many types of data collected from learning platforms. This study used a DNN model to show how deep learning can better understand and predict student behavior.The layered structure of DNNs allows them to automatically find important features and patterns in data, leading to more accurate predictions than traditional methods. When tested on the DeepAdaptEDU dataset, the DNN model performed better than other models, achieving an overall accuracy of 92.3% and strong results for precision, recall, and F1-scores across all levels of adaptation. The model was also good at reliably identifying students with low, medium, and high levels of adaptation, showing how strong and useful it is for real-world online learning settings. The study also highlights how DNN-based methods can help create adaptive learning systems that give teachers and school leaders useful information. Unlike older methods that depend on manually choosing features or making simple assumptions, DNNs can uncover hidden patterns from various types of data, helping to make learning more personalized and effective. Even with these successes, there are still some challenges. The model works best when there's high-quality, labelled data, and it can be hard to explain how it makes decisions, which might make educators hesitant to trust the results. Future work should look into including more time-based data, mixing different types of information, and using explainable AI techniques to improve both accuracy and understanding. In summary, this study shows that Deep Neural Networks are a big step forward in assessing how well students adapt to online learning. By looking at and comparing the best methods available, the research offers a clear path for building smarter, more personalized e-learning systems that can better support students from different backgrounds.

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