

# Review of Machine Learning Models for Application in Adaptive Learning for Higher Education Student

Semen M. Levin

Professor, Department of Automated Control Systems, Tomsk State University of Control Systems and Radio Electronics

## Abstract

The article reviews machine learning models and their application in the context of adaptive learning. The main focus is on the capabilities of adapting models for personalizing the educational process. The article also highlights issues related to the limitations of integrating machine learning into educational systems, including the problems of requiring large datasets and the need for specialized resources. Furthermore, it discusses the challenges in integrating and standardizing these technologies into existing educational systems and considers probable directions for future research. The problems of developing and implementing the technologies described in the article in higher education systems are noted.

**Keywords:** machine learning, adaptive learning, machine learning models, learning management systems, individual-oriented learning, educational technologies, personalized education, educational data analysis, predictive modeling in education, student performance prediction, learning analytics, artificial intelligence in education

## 1. Introduction

In today's society, the evolution of technology and machine learning capabilities have ushered in novel approaches to the educational process and its customization. Adaptive learning, which offers the ability to tailor educational materials and pedagogical methods to the needs and abilities of each student, is increasingly becoming significant and sought-after in the educational landscape [1]. Nevertheless, the effective implementation of this approach necessitates developing and applying machine learning models capable of solving complex data analysis and forecasting tasks, considering many related variables [2]. The exploration of machine learning models used in adaptive learning is a pertinent research direction, as the existing models and methods require adaptation and extension for their application within the context of adaptive learning. Moreover, the development of new models and algorithms focused on the needs of such learning could substantially improve the efficiency of the educational process and, consequently, academic performance [3].

Adaptive learning is a methodology that allows customizing and personalizing the learning process based on each learner's needs and abilities. Unlike traditional mass education, where all students receive the same set of materials and methods, adaptive learning aims to create an optimal educational environment tailored to each learner's individual characteristics [4].

This learning mechanism utilizes data and information about students collected during their learning process to customize and adapt the content, pace, and learning methods. The learning process is optimized by providing students with a personalized approach, tailoring educational materials and methods to their characteristics, and offering feedback and educational support based on their current knowledge and understanding level [5].

## 2. Advantages of Machine Learning

Within the sphere of machine learning models, the implementation of adaptive learning takes on a transformative role, leveraging sophisticated algorithms and data processing techniques to refine the educational experience at a granular level. These models stand at the forefront of educational innovation, offering nuanced insights into each student's learning journey and enabling a highly tailored approach to education. Below are expanded insights into how machine learning models contribute significantly to the realm of adaptive learning:

- **In-depth Personalization of Education:** Beyond merely tailoring educational content, machine learning models delve into the nuances of each student's learning process, considering factors such as pace, learning style preferences, and areas of strength and weakness [6]. This in-depth analysis is made possible by the models' capacity to sift through and interpret extensive datasets, resulting in the design of educational programs and content that are tailored and deeply resonant with the individual learner's educational journey. For example, algorithms can identify patterns in a student's interaction with digital learning materials, enabling the system to recommend resources that match their preferred learning modality (visual, auditory, kinesthetic, etc.).
- **Enhanced Accessibility and Inclusivity:** Machine learning models excel in breaking down barriers to education. By dynamically adjusting content complexity and presentation style, these models can cater to a broad spectrum of learning needs, including those of students with disabilities. For instance, text-to-speech technologies powered by machine learning can provide auditory learning options for visually impaired students, while predictive text input and gesture recognition can aid students with physical disabilities navigate educational software more effectively. This capacity to adapt in real-time creates a more inclusive learning environment, ensuring that educational opportunities are equitable and accessible to all students, regardless of their physical or learning disabilities.
- **Optimization of the Learning Experience:** The application of machine learning to educational data goes beyond simple analysis, venturing into optimization. By continuously evaluating a student's progress, including their academic achievements, behavioural patterns, and expressed preferences, adaptive learning systems can iteratively refine and adjust the learning pathway to suit the evolving needs of the learner [7]. This could manifest in adjusting the difficulty level of tasks in real-time or suggesting breaks and revisions at optimal moments to enhance retention and prevent burnout. Such a dynamic approach ensures that each student's learning trajectory is personalised and optimized for maximum engagement and effectiveness.
- **Predictive Analytics for Proactive Intervention:** Perhaps one of the most compelling uses of machine learning in education is its predictive capability. By analyzing historical and real-time data, these models can forecast future performance trends and identify potential areas of difficulty before they become problematic. This foresight enables educators and the system to intervene proactively, offering additional support, resources, or alternative learning strategies to address the anticipated challenges [8]. For example, suppose a predictive model identifies that a student is likely to struggle

with a forthcoming topic in mathematics. In that case, the curriculum can preemptively adjust to introduce foundational concepts more gradually or suggest supplementary materials to bolster the student's understanding.

Furthermore, machine learning models can also play a critical role in identifying and mitigating broader issues within the educational ecosystem, such as detecting patterns of disengagement or absenteeism and prompting targeted interventions to re-engage students. This holistic application of machine learning not only elevates individual learning experiences but also contributes to improving educational systems at large.

Integrating machine learning models into adaptive learning represents a paradigm shift towards a more personalized, accessible, and efficient educational framework. By harnessing the power of data and analytics, educators are equipped to meet the diverse needs of their students, paving the way for a future where every learner can achieve their full potential.

### 3. Machine Learning Models

Machine learning models can indeed be categorized into what might be termed traditional and conditionally modern. Traditional models form the bedrock upon which current algorithms are built, playing a pivotal role in the development of adaptive learning strategies. They broadly fall into three categories: supervised learning, unsupervised learning, and reinforcement learning, each with distinct methodologies and applications.

**Supervised learning** stands out for its reliance on pre-labelled datasets, which serve as a learning guide for the model to predict new, unseen data [9]. This category includes:

- Linear Regression is primarily used for forecasting and finding relationships between variables.
- Logistic Regression is a go-to method for binary classification problems, distinguishing between two possible outcomes.
- Decision Trees, which segment the dataset into branches to make predictions, offer a visual simplicity that aids in understanding the decision-making process.
- Random Forests is an ensemble method that combines multiple decision trees to improve prediction accuracy and model stability.
- Support Vector Machines (SVM) classify data by finding the optimal hyperplane that separates all data points of one class from those of another [10], showcasing their versatility in handling complex classification tasks.

**Unsupervised learning** dives into unlabeled data, searching for hidden patterns or intrinsic structures. It encompasses:

- Clustering algorithms like K-means, which organize data into clusters based on similarity, are often used for market segmentation, social network analysis, and image segmentation [11].
- Principal Component Analysis (PCA) is a technique for reducing the dimensionality of datasets, increasing interpretability, and minimizing information loss [12].

**Reinforcement Learning** is characterized by trial and error, where an agent learns to make decisions through rewards or penalties. **Q-learning** is a notable method in this category, employing a system that maximizes the expected reward by learning the best action to take in a given state.

In adaptive learning, these traditional models are instrumental in crafting personalized educational paths, designing adaptive assessments, and developing interactive aids that respond to the student's unique learning profile. For instance, supervised learning algorithms have been adept at dissecting the nuances of a

student's learning pace and style, enabling the creation of highly customized educational experiences. Meanwhile, through techniques like clustering, unsupervised learning can categorize students by their knowledge levels or preferences, facilitating a more targeted and effective learning approach [13, 14].

Transitioning to the **conditionally modern models**, we witness the emergence of deep learning, an advanced subset of machine learning that leverages neural networks with multiple layers. This paradigm shift has ushered in groundbreaking developments:

- Transformers and advancements in natural language processing, with models like BERT and GPT-3, have dramatically enhanced machines' ability to comprehend and generate human language, offering unprecedented opportunities in automated content creation, language translation, and sentiment analysis [15].
- Cutting-edge CNN (Convolutional Neural Network) architectures, such as ResNet and Inception, have set new standards in image and video analysis, bolstering facial recognition, autonomous driving, and medical image diagnosis applications [16].
- Generative Adversarial Networks (GANs), a dual-network architecture, have been pivotal in generating photorealistic images, innovating in fields like art creation, video game design, and data augmentation for training machine learning models [17].
- Recurrent Neural Networks (RNNs) and LSTM (Long-Short-Term Memory) units excel at processing sequential data, making them indispensable for analyzing text, predicting time series, and customizing user interactions through personalized recommendations and feedback [18].

These modern advancements expand the horizons of what is possible in machine learning and provide educators with powerful tools to revolutionize adaptive learning. By harnessing these technologies, educational content can be dynamically adjusted to meet the evolving needs of each learner, paving the way for a future where education is more personalized, engaging, and effective.

#### 4. Challenges and Limitations

When juxtaposing the two categories of machine learning models—classical and modern, like deep neural networks—distinct differences emerge, each with unique advantages and challenges. Classical models, lauded for their transparency and simplicity, excel when applied to structured datasets. They rely on apparent, predefined features and relationships, making them ideal for applications where the input data is well-organized, and the underlying patterns are linear or relatively straightforward. For example, linear regression, a staple of classical models, offers clear insights into the relationship between variables, making it invaluable in fields like economics and healthcare for risk assessment and forecasting outcomes based on a set of known variables [19].

Deep neural networks, part of the more contemporary machine learning models, are adept at handling and interpreting the complexity inherent in unstructured data—images, text, and audio—by automatically identifying patterns without explicit programming. This capability is transformative in areas like computer vision and natural language processing, where tasks such as image recognition, language translation, and sentiment analysis benefit from the models' ability to learn nuanced features directly from the data. However, the sophistication of deep learning models comes with the caveat of requiring substantial volumes of data to train effectively. This necessity stems from the models' architecture, which comprises multiple layers of interconnected nodes or neurons that simulate aspects of human brain functionality, enabling them to learn intricate patterns and necessitating extensive examples to achieve high accuracy.

Despite their promise, the deployment of machine learning models in adaptive learning systems is not without its challenges:

- **Data Dependence:** These models' efficacy hinges on access to high-quality, comprehensive datasets. In the educational context, this means detailed records of student interactions, performance metrics, and personalized feedback loops. The challenge lies in gathering sufficient data and ensuring its relevance and diversity to train models that can accurately adapt to a wide range of learning preferences and needs.
- **Resource Intensity:** The infrastructure required to collect, store, and process large datasets, especially for deep learning applications, is significant. Educational institutions must invest in robust computing resources and data storage solutions, which can be a barrier, particularly for those with limited budgets.
- **Expertise Requirement:** Developing, integrating, and maintaining sophisticated machine learning models demands high expertise in data science and machine learning. This requirement translates into a need for skilled professionals who can navigate the complexities of model training, evaluation, and deployment—a resource that is not always readily available in the educational sector.

Educational institutions face global resource constraints, with many universities struggling to allocate funds for advanced adaptive learning projects. The gap in modern infrastructure and the lack of trained personnel to implement and support these technologies underscore a broader challenge in adopting innovative educational tools. Moreover, the inherent resistance to change within the educational ecosystem further complicates the adoption process. Traditional teaching methodologies and curriculums are deeply ingrained, making shifts towards technologically driven, personalized learning approaches a cultural and logistical hurdle.

However, there is a silver lining in the form of the digital-native generation. Having grown up in an era of rapid technological advancement, today's students are more adaptable and open to digital learning solutions. Their familiarity with technology and a natural inclination for digital interactions position them as catalysts for change in educational settings. By leveraging their enthusiasm for tech-driven learning experiences, educational institutions can foster a more receptive environment for implementing machine learning models in adaptive learning systems.

Addressing these challenges requires a multifaceted approach that includes strategic investments in technology, professional development for educators and administrators, and fostering a culture of innovation within the educational sector. By overcoming these barriers, the potential for machine learning to revolutionize education through personalized, efficient, and accessible learning experiences can be fully realized.

## 5. Conclusions

Despite the complexities and limitations highlighted earlier, integrating machine learning models into the educational landscape has the potential to substantially impact teaching and learning practices, positioning them as highly effective pedagogical tools. The challenges of implementing adaptive learning systems based on machine learning models include the need for large volumes of high-quality data, the technical and financial resources required for data collection and storage, and the expertise necessary for creating, integrating, and maintaining these models. Addressing these challenges necessitates a comprehensive strategy encompassing investments in the education and development of human resources, establishing standards and guidelines, and continuously adapting educational programs and methods to incorporate the latest technological advancements.



Moreover, the transition towards adaptive learning powered by machine learning technologies faces additional infrastructure limitations and the scarcity of qualified personnel within many educational institutions. These challenges are compounded by a general resistance to change within the education sector, where both educators and administrative staff may be reluctant to adopt new methodologies and technologies, further complicating the task of transforming established educational processes. However, it is anticipated that the current generation of students, who are digital natives, will be more receptive to and capable of embracing these innovative approaches to learning, thereby accelerating the adoption and integration of machine learning technologies into the educational framework.

In the broader context, successfully incorporating machine learning models into education does not solely hinge on overcoming technical and resource-related challenges but also involves cultivating a cultural shift within educational institutions towards openness, innovation, and continuous improvement. Such a shift would enable educators to leverage the full potential of machine learning to personalize learning experiences, thereby making education more engaging, accessible, and effective for students from diverse backgrounds.

In conclusion, while the path to fully realizing the benefits of machine learning in education may be fraught with obstacles, the potential rewards justify the effort. By adopting a holistic approach that addresses the technical and cultural aspects of innovation in education, stakeholders can lay the groundwork for a transformative impact on educational practices. Integrating machine learning into education should be viewed as a long-term investment that promises to reshape the educational landscape to meet future generations' needs better. It is with optimism that we look forward to these advancements becoming the catalyst for funding, research, and the development of machine learning technologies within university educational processes, heralding a new era of personalized and practical learning.

## 6. Conflict of Interest: None

## 7. References

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