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Applications of deep learning in mathematics education: A review

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Abstract. Traditional classroom settings often fail to account for individual differences, leading to disparities in student performance. Deep learning models offer a solution by analyzing performance data to provide targeted interventions and immediate feedback, thereby personalizing educational experiences. This review examines the transformative potential of deep learning in mathematics education through various applications and methodologies. Studies show that deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can analyze complex student data, identify learning patterns, and offer real-time, personalized support. Notable applications include automated classroom feedback systems, intelligent tutoring systems, and predictive models for student performance. Despite the promising results, challenges such as data quality, computational resources, model interpretability, and potential biases remain. Future research should focus on creating inclusive datasets, improving computational efficiency, and enhancing model transparency to fully harness the benefits of deep learning in educational settings.

Keywords: Mathematics Education, Deep Learning, Classroom, Educational Experience.

1. Introduction

Traditional classrooms often follow a standardized curriculum that does not account for individual differences, resulting in some students falling behind while others are insufficiently challenged. Deep learning models can analyze performance data to identify these gaps and recommend targeted interventions, providing immediate feedback that helps tailor educational experiences to individual needs [1, 2, 3].

Several studies have demonstrated the effectiveness of deep learning in educational settings. One system uses deep learning to analyze classroom recordings and provide automated feedback to teachers, enhancing teacher learning and student engagement in mathematics discussions [4]. Another study shows that deep learning strategies significantly improve academic achievement and practical intelligence among high school students compared to traditional methods [5]. Deep learning has also been used to analyze E-learning platforms, identifying the most effective platforms based on content and usage patterns [6]. Other research found that while deep learning techniques perform comparably to other machine learning methods, they often require more data and computational resources [7]. In higher education, an intelligent system has been proposed using deep learning for functionalities such

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as class attendance monitoring and learning report analysis [8]. Furthermore, combining statistical learning with deep learning has enhanced the accuracy of predicting student learning failures [9]. These studies collectively highlight the transformative potential of deep learning in personalized learning environments. By extracting meaningful insights from educational data, deep learning models create customized learning experiences tailored to each student's needs.

This review explores the principles of deep learning, its role in educational data analysis, and specific applications such as customized assessments, smart evaluation schemes, individualized progress tracking, and immediate feedback mechanisms. Additionally, it addresses challenges and limitations, including issues of interpretability, data privacy, and system integration, while discussing future directions for these technologies in educational settings.

2. Descriptive Statistics of the Literature

Figure 1 illustrates the annual number of papers retrieved using the search terms "Mathematics Education" and "Deep Learning" on Google Scholar. The number of relevant publications has increased steadily from approximately 39,400 in 2010 to over 80,000 in 2022. Notably, there has been a significant surge in research output from 2018 onwards. Although there was a slight decline in 2022, the number of publications remains significantly high, demonstrating sustained interest in this field.

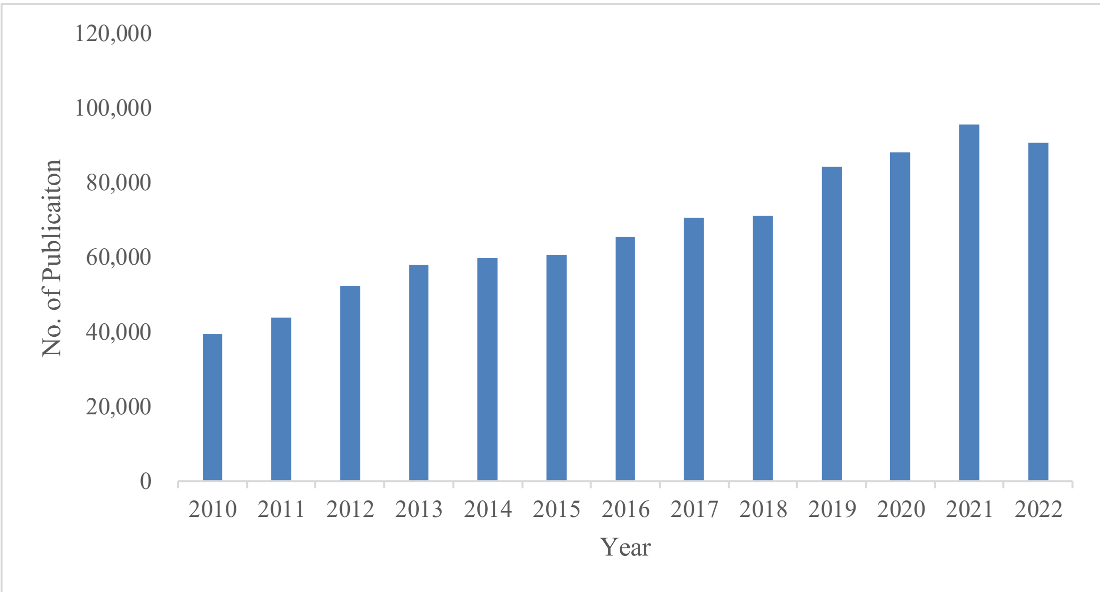

Figure 1. The number of papers searched using "Brain Tumor" and "Deep Learning" per year

3. Background on Personalized Learning in Mathematics Education

3.1. Challenges in Student Data Analysis and Interpretation

Personalized learning in mathematics education faces several challenges, particularly in analyzing and interpreting diverse student data [10, 11]. This data includes numerical scores, textual responses, and behavioral logs, requiring advanced tools for accurate analysis. Standardized tests, while useful, often miss individual learning trajectories and specific struggles, making it hard for educators to offer targeted support.

Additionally, the large volume of data from digital learning platforms can overwhelm traditional methods, causing delays in identifying learning gaps. Ensuring data accuracy and reliability is also crucial, as issues like incomplete records and inconsistent data entry can skew analysis and hinder effective interventions.

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3.2. Role of Deep Learning in Analyzing Student Behavior

Deep learning is a powerful tool for personalized learning, especially in analyzing complex student behavior data. Algorithms like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can process diverse, unstructured data, revealing patterns that traditional methods might miss [12, 13]. For instance, CNNs analyze visual data from handwritten assignments to identify common errors, while RNNs track the progression of a student's problem-solving approach over time, highlighting where difficulties arise. These models integrate multimodal data sources, such as textual responses and interaction logs, providing a holistic view of student engagement and performance. This enables adaptive learning systems to offer personalized feedback and support in real-time.

3.3. Traditional methods versus deep learning approaches

Traditional methods of assessing student performance in mathematics education, such as standardized tests and manual grading, are time-consuming and often lack detailed insights into individual learning trajectories. These methods provide broad overviews of academic achievement but fail to pinpoint specific difficulties, resulting in delayed feedback and limited opportunities for timely intervention.

In contrast, deep learning models offer granular insights into student learning behaviors, enabling more targeted and effective interventions [14]. For example, they can detect whether a student's struggle with algebra is due to issues with quadratic equations, factoring, or word problems, and recommend specific instructional materials to address these gaps. Intelligent Tutoring Systems (ITS) leverage deep learning to provide personalized feedback and tailored instructional support based on real-time performance analysis.

By delivering detailed, real-time insights and personalized learning experiences, deep learning systems transform mathematics education. They improve academic outcomes, enhance student engagement, and provide tailored support that traditional methods cannot match.

4. Machine Learning Models for Mathematics Education

4.1. Algorithms for Mathematics Education

Deep learning models have emerged as powerful tools in the field of education, particularly for enhancing learning outcomes and automating educational processes. By leveraging large datasets and applying sophisticated algorithms, researchers have made significant strides in improving educational effectiveness. These models excel in recognizing complex patterns and extracting relevant features from educational data, thus providing more personalized and effective learning experiences.

A deep learning model combined with Principal Component Analysis (PCA) achieved 92.5% accuracy in predicting student final grades and identifying students needing special attention [15]. Another model, the Deep Neural Networks-based Logical and Activity Learning Model (DNN-LALM), achieved 93% accuracy in detecting logical patterns, enhancing cognitive and task-oriented activities [16]. A hybrid CNN-SVM model for classifying K-12 learning materials achieved 85% accuracy [17]. An automatic checking system using CNN for handwritten numeral recognition reached 91.2% accuracy and reduced teachers' time in checking assignments [18]. An LSTM-based Formula Entailment module was implemented for recognizing entailment between mathematical queries and document formulae [19]. A CNN-LSTM model was utilized to predict student learning outcomes in LMS environments with high accuracy [20]. LSTM and BERT were used for classifying and ranking math problems, achieving up to 75% accuracy with LSTM [21]. Additionally, a deep LSTM technique was employed for the early prediction of learners at risk in self-paced education, achieving high accuracy and precision [22].

These deep learning algorithms not only enhance educational data mining and student performance prediction but also offer potential for personalized learning. This overview sets the stage for exploring the methodologies and results achieved through various deep learning approaches in the subsequent sections.

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4.2. Case studies and real-world applications

Deep learning models have been successfully applied in various educational contexts, demonstrating their potential to enhance teaching methods and learning outcomes. One study introduced a deep learning-based integrated trial-error and STREAM teaching method in college entrepreneurship education, significantly improving students' learning interests and achievements, although it focused only on the geometric characteristics of hyperbolic curves, lacking integration with broader knowledge points [23]. Another system was developed for online recognition of handwritten mathematical expressions using deep bidirectional LSTM and dynamic programming, improving recognition speed while maintaining high accuracy by reordering input strokes and using a modified CYK algorithm [24]. CNNs have also been applied to recognize and evaluate classroom teaching behavior, combining SVM for data extraction and CNNs for behavior recognition, effectively improving identification accuracy and providing consistent evaluations of teaching practices [12]. Additionally, a hybrid 2D CNN model was created to predict student academic performance by transforming 1D numerical data into 2D images, accurately predicting whether students would pass or fail a class, though it did not investigate the impact of individual features on academic performance, indicating an area for future research [25].

These studies highlight the transformative potential of deep learning in education, offering solutions for improving teaching practices, student engagement, and performance prediction. Continued research in this area is essential for further advancements and enhanced educational outcomes.

5. Challenges and Future Directions

Deep learning applications in mathematics education face several significant challenges. One of the primary hurdles is the need for large, high-quality datasets to train models effectively. Mathematics education varies widely across different educational systems and cultural contexts, making it difficult to compile comprehensive datasets that capture this diversity. Additionally, deep learning models require significant computational resources, which may not be readily available in all educational settings, particularly in underfunded schools or regions with limited technological infrastructure. Another challenge is ensuring the interpretability and transparency of deep learning models. Educators and stakeholders need to understand how these models make decisions to trust and effectively integrate them into the curriculum. Furthermore, there's a risk of perpetuating existing biases within educational content and assessment methods, as deep learning models can inadvertently reinforce disparities present in the training data.

To address these challenges, future research and development in deep learning for mathematics education should focus on creating more inclusive and representative datasets. Collaborations between educational institutions worldwide could help gather diverse data that better reflects different teaching methodologies and student populations. Additionally, advancements in computational efficiency could make deep learning tools more accessible, even in resource-limited settings. Enhancing the interpretability of models through explainable AI techniques is crucial for gaining educators' trust and facilitating meaningful use in classrooms. Efforts should also be directed toward developing adaptive learning systems that can personalize instruction based on individual student needs, thereby improving engagement and learning outcomes. Finally, ongoing evaluations of these technologies' impact on educational equity are essential to ensure that they contribute to reducing, rather than exacerbating, existing disparities in mathematics education.

6. Summary

Deep learning models have shown significant promise in transforming mathematics education by providing personalized learning experiences and enhancing teaching methodologies. The ability to analyze diverse and complex student data allows for targeted interventions and real-time feedback, addressing individual learning needs more effectively than traditional methods. However, challenges such as data quality, computational demands, and model interpretability must be addressed to ensure these technologies' equitable and effective integration into educational systems. Future research should prioritize the development of inclusive datasets, advancements in computational efficiency, and

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explainable AI techniques to make deep learning tools more accessible and trustworthy for educators. By overcoming these challenges, deep learning can play a pivotal role in improving educational outcomes and fostering a more personalized and engaging learning environment for all students.

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