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IMPROVING THE EFFICIENCY OF TRAINING ARTIFICIAL INTELLIGENCE MODELS USING NUMERICAL METHODS

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Abstract. This study explores methods for improving the efficiency of training artificial intelligence (AI) models through numerical techniques. The research focuses on optimizing neural networks and sequential models using Gradient Descent, Stochastic Gradient Descent, and Runge–Kutta algorithms. Experimental results demonstrate that numerical approaches significantly enhance model accuracy, reduce error rates, and accelerate the training process. In the context of Uzbekistan, integrating AI models into digital education platforms enables personalized and interactive learning, reduces teachers' workload, and improves student engagement and academic performance.

Keywords: Artificial Intelligence, Numerical Methods, Neural Networks, Model Training, Optimization, Uzbekistan

1. Introduction

In recent years, artificial intelligence (AI) systems have been widely applied across various domains—including education, industry, transportation, and economics—as tools for automating and optimizing complex tasks. The effectiveness of AI models largely depends on the algorithms and computational methods employed during the training process. In particular, efficient utilization of computational resources and improvement of model accuracy are crucial when dealing with large-scale datasets and complex neural networks.

Numerical methods play a critical role in training AI models. Optimization algorithms such as Gradient Descent, Stochastic Gradient Descent, and Runge–Kutta enable efficient parameter updates and accelerate the training process. These approaches help reduce prediction errors and improve the reliability of AI systems.

In Uzbekistan, significant attention is being paid to digital transformation and the development of e-learning platforms. The integration of AI-based systems into educational institutions is expanding, offering opportunities to personalize learning processes, monitor individual student progress, and enhance interactivity. Therefore, improving the efficiency of AI model training using numerical methods is both scientifically and practically relevant.

This study examines the methodology of training AI models using numerical approaches, evaluates their effectiveness, and explores their practical applications in the educational context of Uzbekistan.

2. Methods

The objective of this study is to evaluate the effectiveness of training AI models using numerical methods. Python and MATLAB programming environments were utilized for model development and training. The dataset consisted of students' test scores, essay results, and individual performance indicators. Data preprocessing included cleaning, normalization, and transformation into suitable formats for model training.

Several AI models were implemented in this study. Multi-Layer Perceptron (MLP) models were used for predicting student performance, while Long Short-Term Memory (LSTM) networks were applied for time-series analysis. Additionally, classical regression models were employed to identify key factors influencing test outcomes.

Numerical methods played a central role in the training process. Gradient Descent and Stochastic Gradient Descent algorithms were used for iterative parameter updates and error minimization. In LSTM models, the Runge–Kutta method was applied to enhance stability in handling temporal data. These approaches enabled faster training, efficient use of computational resources, and improved prediction accuracy.

Model performance was evaluated using metrics such as Accuracy, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and stability indicators. Visualization tools in Python (Matplotlib, Seaborn) and MATLAB were used to present results graphically. The models were also tested within digital educational platforms in Uzbekistan to assess their impact on personalized learning, interactivity, and teacher workload reduction.

3. Results

The results indicate that numerical methods significantly improve the efficiency of training AI models. When MLP models were trained using Gradient Descent, accuracy reached 91%, while the use of Stochastic Gradient Descent increased accuracy to 93%. This improvement is attributed to effective parameter optimization and reduced training error.

In LSTM models, the application of Runge–Kutta and SGD algorithms reduced the RMSE to 0.08 and significantly enhanced model stability. Classical regression models achieved prediction accuracy levels of 88–90% after optimization through numerical techniques.

Furthermore, the use of Stochastic Gradient Descent accelerated the training process by 25–30% compared to traditional Gradient Descent, demonstrating improved computational efficiency. The Runge–Kutta method enhanced stability in time-series modeling, making it suitable for real-time monitoring systems.

In the Uzbek educational context, experimental implementation showed that automated evaluation of test and essay results reduced teacher workload. Personalized learning pathways improved student engagement and motivation, while interactive digital platforms enhanced overall learning effectiveness. Visualization of results using Python and MATLAB clearly illustrated performance improvements achieved through numerical methods.

4. Discussion

The findings confirm that numerical methods substantially improve the efficiency of AI model training. Gradient Descent and Stochastic Gradient Descent algorithms enhance accuracy and reduce errors, with SGD being particularly effective for large-scale datasets due to its computational efficiency.

The application of the Runge–Kutta method in LSTM models improves stability in time-series analysis and supports real-time applications. Integration of AI models into digital education platforms in Uzbekistan has demonstrated benefits such as reduced teacher workload, increased interactivity, and improved personalization of the learning process.

However, several limitations were identified. Training AI models requires significant computational resources, especially when working with large datasets. Additionally, the lack of standardized data across educational institutions makes generalization of results more challenging.

Future research should focus on combining numerical methods, implementing adaptive optimization algorithms, and expanding standardized datasets in Uzbekistan. These improvements will further enhance AI-driven educational systems and support modernization of the learning process.

5. Conclusion

This study demonstrates that numerical methods significantly improve the efficiency of training artificial intelligence models. Techniques such as Gradient Descent, Stochastic Gradient Descent, and Runge–Kutta enable faster training, higher accuracy, and reduced error rates. The performance of MLP and LSTM models in prediction tasks has notably improved.

In the context of Uzbekistan, integrating AI models into digital education platforms supports personalized and interactive learning while reducing teachers' workload. Predictive analytics based on student performance enhances motivation and educational outcomes, aligning with national strategies for educational modernization.

Future studies should explore adaptive optimization techniques, large-scale data processing, and standardization of educational datasets to further improve AI applications in education.

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