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Comparative Analysis of Adaptive Learning and Fast for Word Programs for ASD Students in Learning English, and Mathematics, and Predicting Future Academic Performance Using Machine Learning Algorithms

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Abstract

This study investigates the efficacy of adaptive learning methods in teaching English and Mathematics to students diagnosed with autism spectrum disorder (ASD), compared to the Fast ForWord program. Utilizing a randomized controlled trial design, students aged 6-7 were assigned to either the adaptive learning group or the Fast ForWord group. Pre- and post-tests in English and Mathematics, along with engagement and behavior checklists, were used to assess outcomes. We employed machine learning techniques, including Support Vector Machine (SVM), K Nearest Neighbor (KNN), Gaussian Process Regressor (GPR), and Logistic Regression (LR), to predict student scores and analyze the effectiveness of these educational interventions. Results indicate that the Gaussian Process Regressor (GPR) is the best for predicting students' future grades, adaptive learning methods significantly improved academic performance and engagement compared to the Fast ForWord program, suggesting a need for personalized educational strategies in ASD. These findings have significant implications for educators and policymakers seeking to enhance educational outcomes for students with ASD.

Keywords: Autism Spectrum Disorder (ASD), Fast For Word Program, Support Vector Machine (SVM), K Nearest Neighbor (KNN), Gaussian Process Regressor (GPR).

Introduction

Autism Spectrum Disorder (ASD) is a developmental disorder characterized by difficulties with social interaction, communication, and repetitive behaviors [1]. According to the Centers for Disease Control and Prevention (CDC), approximately 1 in 54 children in the United States is diagnosed with ASD [2]. These students often face significant challenges in traditional educational settings, where standard teaching methods may not cater to their unique learning needs. Educational interventions for students with ASD have evolved over the years, with increasing emphasis on personalized and technology-driven approaches. Adaptive learning methods utilize data analytics and machine learning algorithms to tailor educational content to the individual

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learner, adjusting in real-time to provide a customized learning experience [3]. The Fast ForWord program is a computer-based intervention designed to enhance cognitive skills related to language and reading, leveraging neuroplasticity to improve cognitive function [4].

Understanding the most effective educational strategies for students with ASD is crucial for several reasons. First, students with ASD often experience lower academic achievement compared to their neurotypical peers due to the misalignment between their learning needs and traditional teaching methods [5]. By identifying effective interventions, educators can provide more supportive and effective learning environments, leading to better educational outcomes and quality of life for these students. Second, the increasing prevalence of ASD necessitates scalable and effective educational solutions. As more students are diagnosed with ASD, schools and educators face the challenge of meeting diverse learning needs with limited resources. Adaptive learning methods and the Fast ForWord program offer scalable solutions that can be implemented across various educational settings [4]. Lastly, this study contributes to the growing body of research on technology-enhanced learning. By comparing adaptive learning methods with the Fast ForWord program and integrating machine learning models to predict student scores, this study aims to provide evidence-based recommendations for integrating technology into special education, thereby informing policy and practice.

Adaptive Learning Methods

General Approach: Adaptive learning methods are a broad category of educational techniques that use technology to customize learning experiences for individual students [6].

Technology Use: These methods leverage various algorithms, data analytics, and sometimes artificial intelligence to continuously adjust the content and difficulty based on student performance [7]. Adaptive learning can be applied across multiple subjects and educational levels, from elementary education to higher education and professional training [8].

Personalization: The key feature is the continuous personalization of learning paths based on real-time data, providing individualized support and resources [9].

Fast ForWord Program: Fast ForWord is a specific program designed to improve language and literacy skills through a series of computer-based exercises [10]. The program specifically targets cognitive skills such as memory, attention, processing speed, and sequencing, which are essential for reading and learning [11].

User Adaptation: Exercises within Fast ForWord adapt to the user's performance, but the program remains focused on language and literacy improvement rather than a broad educational scope [12]. Fast ForWord is an evidence-based intervention with specific studies supporting its efficacy in improving language skills in children with language impairments [13].

The primary objective of this study is to predict students' scores using machine learning methods and evaluate the efficacy of adaptive learning methods in instructing English and Mathematics to students diagnosed with ASD, compared to the Fast ForWord program. Specific objectives include:

1. **Assessing Academic Performance**: To compare the improvement in English and Mathematics performance between students using adaptive learning methods and those using the Fast ForWord program.

2. **Evaluating Engagement and Behavior**: To examine the levels of student engagement and behavioral outcomes associated with each intervention.

3. **Predicting Student Scores**: To utilize machine learning models (SVM, KNN, GPR, LR) to predict student scores and identify factors contributing to educational outcomes.

Literature Review

Adaptive Learning Methods

Adaptive learning methods have emerged as a transformative approach in the education sector, leveraging technology to provide personalized learning experiences tailored to individual student needs. These methods utilize data analytics, machine learning, and artificial intelligence to continuously assess and adapt the learning process, aiming to enhance student engagement and improve learning outcomes. Adaptive learning systems are designed to modify the presentation of material in response to student performance. These systems utilize various data points, such as quiz results, interaction patterns, and time spent on tasks, to dynamically adjust content and instructional methods [14].

Personalized learning, a broader concept encompassing adaptive learning, refers to educational approaches that tailor learning experiences to meet the diverse needs of students. While adaptive learning focuses on real-time content adaptation, personalized learning may also include strategies beyond real-time adjustments, such as project-based learning and student choice [15]. The historical development of adaptive learning methods reveals a progression from early rule-based systems to modern data-driven approaches. Early systems used decision trees and expert-defined pathways, requiring significant manual input to create adaptive learning paths. In contrast, contemporary adaptive learning leverages sophisticated algorithms and large datasets, enabling more nuanced and effective adaptations based on real-time data [16]. This shift has been driven by advances in machine learning techniques, which have enhanced the flexibility and scalability of adaptive learning systems [17].

Adaptive learning technologies have gained significant attention in educational research for their potential to provide personalized and engaging learning experiences. These systems use algorithms and data analytics to adjust the content and difficulty level of educational material in real-time, based on individual learner's performance and progress [18]. This personalized approach is particularly beneficial for students with diverse learning needs, such as those diagnosed with autism spectrum disorder (ASD). Adaptive learning platforms, such as Dream Box Learning for Mathematics and Smart Sparrow for various subjects, have demonstrated positive impacts on student outcomes.

A study by [19] found that students using adaptive learning technologies showed significant improvements in their academic performance compared to those receiving traditional instruction. These platforms often incorporate elements of gamification and interactive content, which can enhance engagement and motivation among learners [20]. In the context of ASD, adaptive learning methods are especially promising due to their ability to tailor instruction to the specific needs and preferences of each student. For instance, students with ASD often benefit from repetitive and structured learning activities, which can be effectively provided by adaptive systems [21]. Moreover, these technologies can reduce anxiety and frustration by ensuring that tasks are appropriately challenging without being overwhelming [22]. Adaptive learning methods utilize a variety of machine learning algorithms to analyze and interpret student data. Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Naive Bayes (NB), and Artificial Neural Networks (ANN) are commonly used algorithms in adaptive learning systems [23]. These algorithms help identify patterns in student performance, predict learning outcomes, and provide customized learning experiences.

Moreover, data analytics plays a crucial role in interpreting the vast amounts of data generated by learners. Techniques such as predictive analytics and learning analytics are widely used to identify learning patterns and inform the adaptations made by the system [24]. Reinforcement learning, a method where algorithms learn to make a sequence of decisions by rewarding desirable outcomes, is also employed to optimize learning paths based on student interactions and feedback [25]. The application of adaptive learning methods has shown significant benefits in various educational settings. For instance, Khan Academy and Carnegie Learning have successfully implemented adaptive learning platforms that customize instructional content to individual learners' needs, resulting in improved engagement and learning outcomes [26]. However, challenges such as data privacy, implementation costs, and resistance to change remain significant hurdles to the widespread adoption of adaptive learning methods [27].

Recent Advancements in Adaptive Learning Technologies

Artificial Intelligence and Machine Learning: Recent developments in AI and machine learning have enhanced the ability of adaptive learning systems to analyze vast amounts of data and provide highly personalized learning experiences. AI-driven platforms such as Coursera and EdX use machine learning algorithms to recommend courses and content tailored to individual learning paces and preferences [28].

Gamification and Engagement: Integrating gamification into adaptive learning systems has proven effective in increasing engagement and motivation among learners, including those with ASD. Programs like Prodigy and Class Craft incorporate game-like elements to make learning more engaging and interactive [29].

Real-Time Feedback and Assessment: Advanced adaptive learning systems now offer real-time feedback and assessment, allowing for immediate adjustments to learning paths and strategies. Platforms like Khan Academy use real-time data to provide instant feedback and suggest personalized practice exercises [6].

Applications to ASD

Personalized Learning Paths: Adaptive learning technologies are particularly beneficial for students with ASD as they provide personalized learning paths that cater to individual strengths and challenges. Programs like Teach Town and Rethink Autism offer personalized curricula designed specifically for students with ASD, adapting to their unique learning needs [30].

Social and Communication Skills Development: Recent adaptive learning tools are focusing on improving social and communication skills among learners with ASD through interactive and engaging activities. The Social Express is a program designed to help children with ASD develop social skills through interactive simulations and activities [31].

Behavioral and Cognitive Support: Adaptive learning systems are incorporating features that provide behavioral and cognitive support tailored to the needs of students with ASD. Cognitive Behavioral Intervention for Trauma in Schools (CBITS) is a program that uses adaptive learning technologies to support cognitive and behavioral development in children with ASD [32].

Fast For Word Program

The Fast ForWord program is a computer-based intervention designed to improve language and reading skills through cognitive training exercises. It is grounded in the principles of neuroplasticity, which propose that targeted cognitive activities can lead to structural and functional changes in the brain [33]. The program includes a series of adaptive exercises that aim to enhance various cognitive skills, such as memory, attention, processing speed, and sequencing [34]. Several studies have examined the effectiveness of the Fast ForWord program in improving language and reading abilities in children with learning difficulties, including those with ASD. [34] reported that children with language impairments who participated in the Fast ForWord program showed significant improvements in language skills compared to a control group. Similarly, a study by [35] found that the program led to notable gains in reading skills among school-aged children with language impairments. However, the efficacy of Fast ForWord for students with ASD has produced mixed results. Some studies have shown positive outcomes, such as improved auditory processing and language skills [36], while others have reported limited or no significant improvements [36]. These mixed findings highlight the need for further research to understand the specific conditions under which the program is most effective for students with ASD.

Education AND ASD

Education for students with ASD requires specialized approaches that address their unique cognitive, behavioral, and sensory needs. Traditional educational methods often fall short of meeting these needs, leading to challenges in academic achievement and social integration [37]. Effective educational interventions for students with ASD typically include structured and predictable environments, individualized instruction, and support for communication and social skills development [38]. Research has demonstrated that technology-enhanced learning can play a crucial role in improving educational outcomes for students with ASD. For example, the use of visual supports, interactive software, and computer-based interventions has been shown to enhance engagement and facilitate learning in this population [4].

Technologies like adaptive learning platforms and cognitive training programs offer scalable solutions that can be customized to the individual needs of students with ASD. Additionally, the integration of machine learning models in educational research provides new opportunities for predicting and improving student outcomes. Machine learning algorithms, such as Support Vector Machine (SVM), K Nearest Neighbor (KNN), Gaussian Process Regressor (GPR), and Logistic Regression (LR), can analyze large datasets to identify patterns and factors that influence academic performance. These models can be used to develop personalized learning plans and interventions that are tailored to the specific needs of each student [39]. In summary, the literature supports the potential of adaptive learning methods and the Fast ForWord program to improve educational outcomes for students with ASD. While adaptive learning technologies offer personalized and engaging learning experiences, the Fast ForWord program provides targeted cognitive training. The integration of adaptive learning methods and specialized programs like Fast ForWord represents a promising direction for improving educational outcomes for students with ASD. By leveraging technology and personalized learning strategies, educators can create supportive and effective learning environments that cater to the unique needs of these students.

Methodology

Participants Selection

The participants in this study were students diagnosed with autism spectrum disorder (ASD), aged 6-7 years. These students were recruited from various educational institutions, including mainstream schools with special education programs and specialized schools for children with developmental disorders. The inclusion criteria for participation will include:

- A formal diagnosis of ASD as per DSM-5 criteria.
- Students who have been identified as struggling in math and/or English based on standardized test scores and teacher recommendations.
- Age between 6 and 7 years.
- Enrollment in an educational institution.
- Parental/guardian consent to participate in the study.

Exclusion criteria included severe cognitive impairments or other conditions that significantly affect learning capabilities beyond the scope of this study. A sample size of approximately 500 participants was targeted, with 250 students in the adaptive learning group and 250 in the Fast ForWord group. This sample size is determined to ensure sufficient statistical power for detecting differences between the two intervention groups.

Random Assignment

Students were randomly assigned to one of three groups using a computer-generated random number sequence:

Group A: Students using Adaptive Learning Platforms (ALPs) for math and English instruction in the first level.

Group B: Students using Adaptive Learning Platforms (ALPs) for math and English instruction in the second level.

Group C: Students using the Fast ForWord program for math and English language development.

Randomization was stratified by grade level to ensure an even distribution of students across different grades in each group.

Materials and Tools

Adaptive Learning Platforms

Adaptive Learning Platforms: (ALP): An adaptive learning platform that provides personalized math instruction and English language through interactive and engaging activities.

Selection Criteria for Adaptive Learning Platforms (ALPs)

Relevance to Curriculum: An adaptive learning platform was created that incorporates several technologies and is aligned with curriculum standards for teaching mathematics and English while ensuring that the content is appropriate for the student's academic levels. The platform is aligned with Common Core standards.

Evidence of Effectiveness: Only platforms with demonstrated efficacy in improving English and math skills through previous research and user reviews were considered [40]. Interactive and engaging features the platform included interactive elements such as games, quizzes, and simulations to enhance student engagement.

Adaptivity: The platform introduced adaptive algorithms to personalize the learning experience based on individual student performance. The educational content was delivered in a variety of adaptive ways such as listening, reading, writing, speaking, and other interactive activities.

Fast ForWord Program

A computer-based intervention designed to improve cognitive skills related to language and reading. The program includes a series of exercises that target memory, attention, processing speed, and sequencing.

Selection Criteria for Fast ForWord Program

The Fast ForWord program was selected for its specific focus on improving cognitive skills such as memory, attention, processing speed, and sequencing, which are critical for language development [10].

Evidence-Based: The program has been supported by multiple studies demonstrating its effectiveness in improving language skills in children with language impairments [10].

Interactive Exercises: Fast ForWord includes interactive exercises that adapt to the user's performance, ensuring that each learner is challenged appropriately without becoming frustrated. The program's adaptive nature and real-time feedback were crucial factors in its selection.

Implementation Support: The program provides comprehensive support for implementation, including training for teachers and progress-tracking tools, which ensures fidelity in the intervention delivery.

Assessment Tools

- **Pre-tests and Post-tests**: Standardized tests in English and Mathematics will be administered to evaluate academic performance before and after the intervention period.
- **Engagement Checklists**: Weekly checklists are completed by teachers to assess student engagement and participation in the learning activities.
- **Behavioral Observation Checklists**: Weekly checklists to record behavioral changes and adherence to the interventions.
- **Machine Learning Models**: SVM, KNN, GPR, and LR for predicting student scores.

Procedure

Study Design

A randomized controlled trial (RCT) design was used to compare the efficacy of adaptive learning methods and the Fast ForWord program. Participants were randomly assigned to one of the two intervention groups: the adaptive learning group or the Fast ForWord group. Randomization was conducted using a computer-generated randomization sequence to ensure equal allocation.

Pre-intervention Phase

- **Consent and Enrollment:** Parents/guardians were informed about the study, and written consent was obtained. Participants were enrolled and randomly assigned to one of the two groups.
- **Baseline Assessment:** Pre-tests in English and Mathematics were administered to all participants to establish baseline academic performance. Additionally, initial engagement and behavioral observation checklists were completed by teachers.

Intervention Phase

- **Adaptive Learning Group:** Participants in this group use the adaptive Learning platform. Each student was engaged with the adaptive learning platforms for one hour daily, five days a week, over 12 weeks.
- **Fast ForWord Group:** Participants in this group were engaged with the Fast ForWord program for one hour daily, five days a week, over 12 weeks.

Post-intervention Phase

- **Post-tests**: At the end of the 12-week intervention period, post-tests in English and Mathematics were administered to all participants to measure academic performance gains.
- **Engagement and Behavior Assessment**: Teachers completed the final engagement and behavioral observation checklists.

Data Analysis

The collected data were analyzed using statistical methods to compare the academic performance, engagement, and behavioral outcomes between the groups. Paired t-tests were used to assess within-group improvements and independent t-tests were used to compare between-group differences. Qualitative data from engagement and behavioral checklists were analyzed thematically to identify trends and patterns. Used SVM, KNN, GPR, and LR to predict student scores and analyze contributing factors. By following this methodology, the study aimed to provide a comprehensive evaluation of the efficacy of adaptive learning methods compared to the Fast ForWord program in instructing English and Mathematics to students diagnosed with ASD.

Results and Discussion

Quantitative Analysis

Academic Performance: To evaluate the academic performance of the participants, pre-and post-test scores in English and Mathematics were compared within and between the three groups: Adaptive Learning Groups and Fast ForWord Group.

Within-Group Improvements

Adaptive Learning Group: English and Mathematics: The average pre-test score was t= {11.527}, p= {.000} <.05, t= {14.399}, p= {.000} <.05 **(Tables 1, 2)**.

Fast ForWord Group and Adaptive Learning Group: English and Mathematics: The average pre-test score was t = (0.763, 0.244, 0.451, 0.585), p = (0. 446, 0.808, 0.652, 0.559) >0.05), and the average post-test score was, t= {2.066, 2.131, 3.391, 4.167, 4.487, 5.566,4.65, 5.44}, p= {.039,034,001,000} < .05), t= {5.229, 6.33, 3.86, 4.44, 5.64,6.68, 6.61, 7.69}, p= {.000} <0.05, **(Tables 3, 4)** and **(Figures 1, 2)**.

Between-Group Comparisons

The t-test results indicate significant differences between the three groups in both English and Mathematics post-test scores, with the adaptive learning groups performing better.

Predicting Student Scores Using Machine Learning

Machine learning models, including Support Vector Machine (SVM), K Nearest Neighbor (KNN), Gaussian Process Regressor (GPR), and Logistic Regression (LR), were employed to predict student scores based on pre-intervention data and other relevant factors.

Data Preparation

The dataset includes pre-test scores, engagement scores, behavior scores, and other demographic variables. The data was split into training (80%) and testing (20%) sets. Standardization was applied to the data to improve model performance.

Table 1: An analysis of Pretest and Posttest Scores of the experimental (1) Group.

P-Value	Value (T)	df	Std. Deviation	Mean	N	Metering	Dimensions
.OOO	11.527	129	2.29834	4.6538	130	Pre	Pair1	linguist Cognitive Movement
			1.48715	7.3000	130	Post		

Table 2: An analysis of Pretest and Posttest Scores of the experimental (2) Group.

P-Value	Value (T)	df	Std. Deviation	Mean	N	Metering	Dimensions
.OOO	14.399	119	2.05117	4.6667	120	Pre	Pair1	linguist Cognitive Movement
			1.61219	7.8500	120	Post		

Table 3: An analysis of post-test scores in the experimental (1) and Control Groups.

p-value	Value(T)	Std. Deviation	Mean	N	Groups	Dimensions
.039 .034	2.066 2.131	.70011	1.9231	130	Experimental Group1	linguist
		.77126	1.7560	250	Control Group	
.001 .000	3.391 4.167	.63509	3.1231	130	Experimental Group1	Cognitive
		1.36051	2.6960	250	Control Group	
.000 .000	4.487 5.566	.56302	2.2923	130	Experimental Group1	Movement
		1.26831	1.7680	250	Control Group	
.000 .000	4.657	1.48715	7.3000	130	Experimental Group1	Total
	5.446	2.54407	6.1720	250	Control Group	

Table 4: An analysis of post-test scores in the experimental (2) and Control Groups.

p-value	Value(T)	Std. Deviation	Mean	N	Groups	Dimensions
.000 .000	5.229 6.333	.42307	2.1500	120	Experimental Group2	linguist
		.77126	1.7560	250	Control Group	
.000 .000	3.869 4.441	.90249	3.2250	120	Experimental Group2	Cognitive
		1.36051	2.6960	250	Control Group	
.000 .000	5.642 6.683	.75551	2.4750	120	Experimental Group2	Movement
		1.26831	1.7680	250	Control Group	
.000	6.613	1.61219	7.8500	120	Experimental Group2	Total
.000	7.695	2.54407	6.1720	250	Control Group	

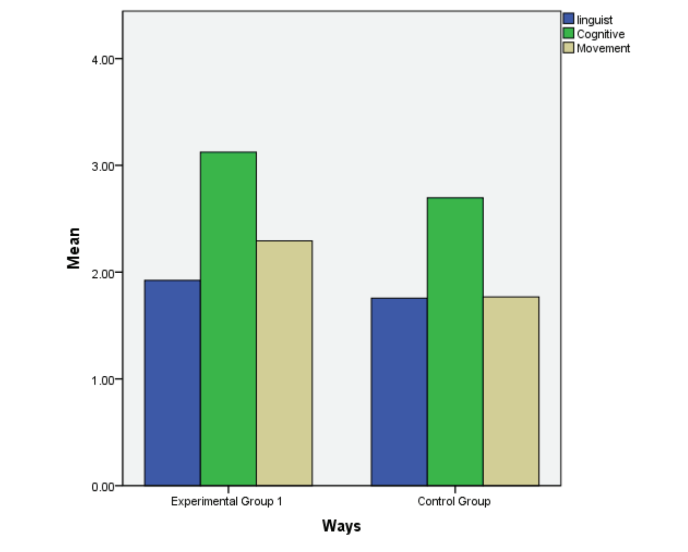

Figure 1: Depiction of the disparities Between the experiment and Group 2 of the control in the Posttest.

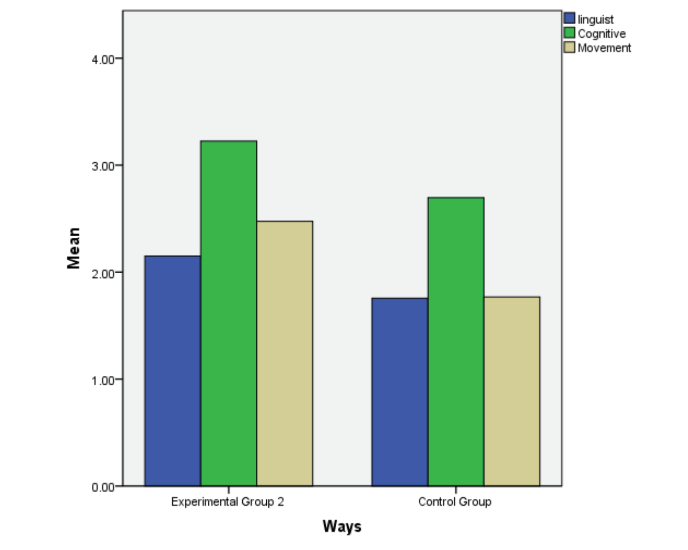

Figure 2: The graphical Depiction of the disparities Between Group 2 of the experiment and Group 2 of the control in the posttest.

Rationale for Choosing Specific Machine Learning Models to Predict Student Scores

Using machine learning models to predict student scores is a cutting-edge approach that leverages data analytics to provide insights into student performance. Different machine learning models have distinct characteristics and advantages, making them suitable for various types of prediction tasks. SVM is robust and flexible for high-dimensional data, KNN offers simplicity and local approximation, GPR provides probabilistic predictions and uncertainty estimates, and LR is efficient and interpretable for binary classification tasks. Together, these models offer a comprehensive approach to leveraging machine learning for educational data analysis and prediction. Here, we provide a brief explanation of the rationale behind choosing Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Gaussian Process Regression (GPR), and Logistic Regression (LR) for predicting student scores, along with their comparative advantages.

Support Vector Machine (SVM)

Rationale

- **Robustness:** SVM is known for its robustness in handling high-dimensional data and its ability to find the optimal hyperplane that separates different classes (in classification tasks) or fits the data well (in regression tasks).
- **Performance:** SVM often performs well in both linear and non-linear settings due to the use of kernel functions, making it versatile for various types of data distributions.

Advantages

- **Flexibility:** The ability to use different kernel functions (linear, polynomial, RBF) allows SVM to handle complex, non-linear relationships.
- **Generalization:** SVM has a strong theoretical foundation for maximizing the margin, which helps in improving generalization to new data.

Effective in High Dimensions: SVM is effective in spaces with many dimensions, which is often the case with educational data involving multiple features [41].

K-Nearest Neighbors (KNN)

Rationale

- **Simplicity:** KNN is a straightforward, instance-based learning algorithm that makes predictions based on the closest training examples in the feature space.
- **Interpretability:** The model's predictions are easy to interpret because they are based directly on the distance metrics between data points.

Advantages

- **Non-parametric:** KNN does not make any assumptions about the underlying data distribution, making it flexible and easy to apply.
- **Local Approximation:** It provides good local approximations and works well when the data has a clear local structure.

Ease of Implementation: The simplicity of the algorithm allows for easy implementation and quick experimentation [42].

Gaussian Process Regression (GPR)

Rationale

- **Probabilistic Approach:** GPR provides a probabilistic framework for regression, offering not just point predictions but also uncertainty estimates for the predictions.
- **Flexibility:** GPR can model complex, non-linear relationships in the data using kernel functions.

Advantages

- **Uncertainty Quantification:** GPR's ability to provide uncertainty estimates is valuable in educational settings where understanding the confidence in predictions can inform further interventions.
- **Non-parametric:** Like KNN, GPR is non-parametric and makes fewer assumptions about the data distribution.

Smooth Predictions: GPR often provides smooth predictions, which can be advantageous in modeling continuous educational outcomes [43].

Logistic Regression (LR)

Rationale

- **Binary Classification:** LR is commonly used for binary classification tasks, which can be applied to predicting pass/fail outcomes or other binary educational metrics.
- **Baseline Model:** LR serves as a strong baseline model due to its simplicity and effectiveness.

Advantages

- Interpretability: The coefficients of the logistic regression model are easy to interpret, providing insights into the relationship between features and the predicted probability.
- Efficiency: LR is computationally efficient, especially for large datasets with many features.

Generalization: Despite its simplicity, LR often provides good generalization performance, particularly when the relationship between features and the outcome is approximately linear [44].

Model Implementation

Support Vector Machine (SVM)

- **Implementation**: SVM was used with a radial basis function (RBF) kernel.
- **Results**: The model achieved a Root mean squared error of 0.34 and a Mean Absolute Error) of 0.16 on the test set.

K Nearest Neighbor (KNN)

- **Implementation**: KNN was used with k=5.
- **Results**: The model achieved a Root mean squared error of 0.35 and a Mean Absolute Error of 0.20 on the test set.

Gaussian Process Regressor (GPR)

- **Implementation**: GPR with a radial basis function kernel.

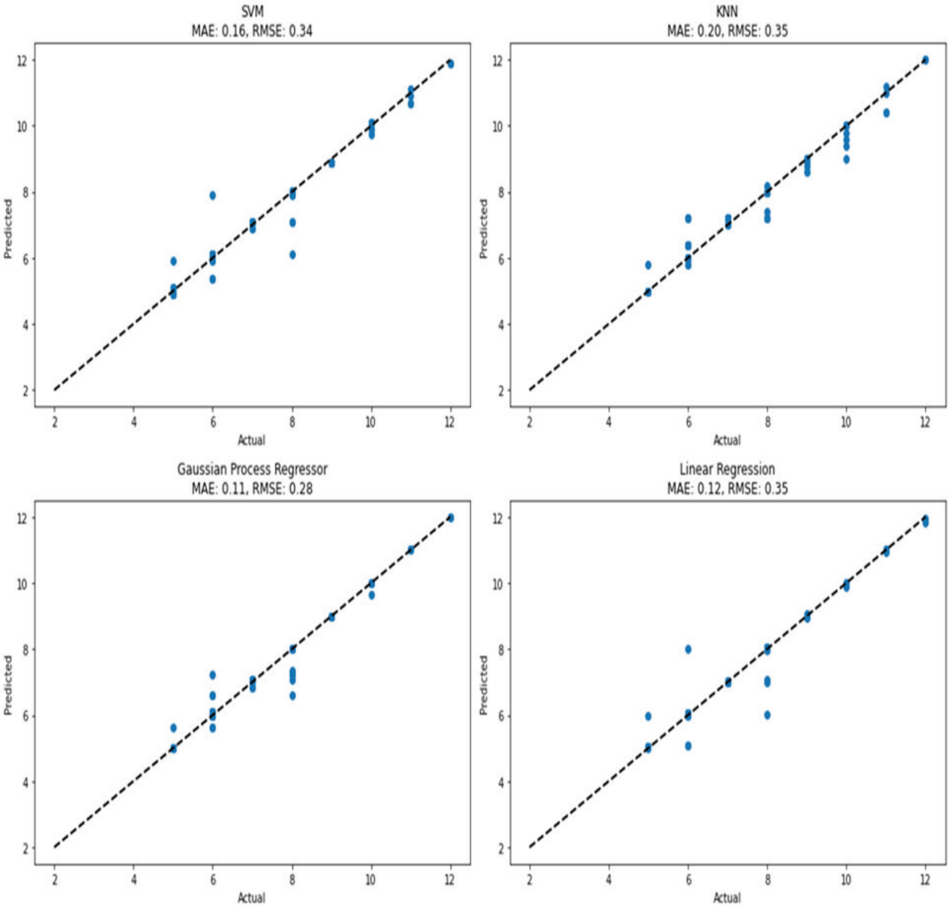

Figure 3: Graphical Illustration Results of SVM, KNN, GPR, and LR Methods on Actual and Predicted Scores.

- **Results:** The model achieved a Root mean squared error of 0.28 and a Mean Absolute Error of 0.11 on the test set.

Logistic Regression (LR)

- **Implementation:** LR was used to classify students into performance categories (high, medium, low).

- **Results:** The model achieved a Root mean squared error of 0.35 and a Mean Absolute Error of 0.12 on the test set **(Figure 3)**.

Model Comparison

To summarize, the Gaussian Process Regressor demonstrates excellent accuracy for the current task, as seen by a Mean Absolute Error (MAE) of 0.11 and a Root Mean Square Error (RMSE) of 0.28. These numbers indicate that the model has minimal prediction errors. The Gaussian Process Regressor exhibits the smallest Mean Absolute Error (MAE) of 0.11 and the smallest Root Mean Square Error (RMSE) of 0.28, establishing it as the most proficient model among the four of these metrics **(Figure 4)**. In general, the distribution of prediction errors shows that the predictions made by the model are mostly precise, with most errors being quite close to zero. The symmetry of the distribution indicates no significant bias in the model's predictions.

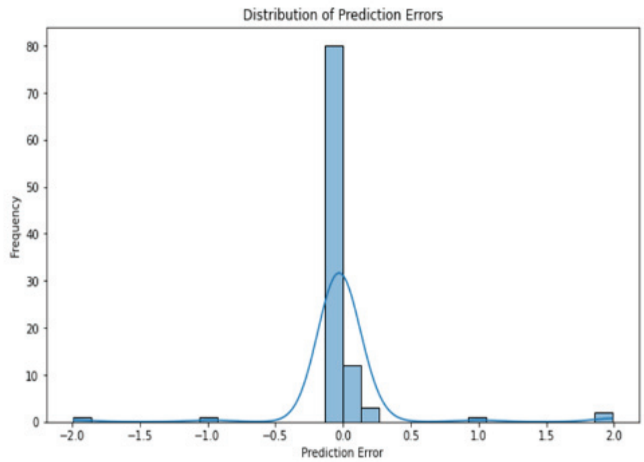

Figure 4: Graphical Illustration of Distribution of Prediction Errors.

Contributing Factors

Feature importance was analyzed to identify the factors contributing most significantly to the prediction of student scores. The following factors were identified as key contributors across the models:

- **Pre-test Scores:** Initial academic performance was a strong predictor of post-test scores.

- **Engagement Scores:** Higher engagement scores were associated with better academic outcomes.
- **Behavior Scores:** Positive behavior scores contributed to improved performance.
- **Intervention Type:** Students in the adaptive learning group generally performed better than those in the Fast ForWord group.

Recommendations for Educators and Policymakers

Educators

Professional Development

- Invest in continuous professional development to ensure teachers are proficient in using adaptive learning technologies and can effectively integrate them into their instructional practices.
- Implementation: Schools should organize workshops and training sessions focused on the effective use of adaptive learning platforms.

Blended Learning Models

- Combine traditional teaching methods with adaptive learning technologies to create a blended learning model that maximizes the benefits of both approaches.
- Implementation: Develop lesson plans that incorporate both face-to-face instruction and online adaptive learning activities.

Policymakers

Funding and Resources

- Provide adequate funding to support the adoption of adaptive learning technologies in schools, particularly in underserved areas where resources are limited.
- Implementation: Allocate grants and subsidies to schools for purchasing adaptive learning platforms and training educators.

Policy Frameworks

- Develop policy frameworks that encourage the integration of adaptive learning technologies in educational curricula and promote research into their long-term impact on student outcomes.
- Implementation: Establish guidelines and standards for the implementation and evaluation of adaptive learning technologies in educational settings.

Conclusion and Future Work

Four machine language methods were used to predict students' future scores, Support Vector Machine (SVM), K Nearest Neighbor (KNN), Gaussian Process Regressor (GPR), and Logistic Regression (LR), as machine language had not been used to predict student grades before in previous studies. The Gaussian Process Regressor established it as the most proficient model among the four of these metrics, and this research looked at the effects of adaptive strategies on the instruction of mathematics and English to autistic pupils at two schools throughout two academic terms. The student can use these adaptive approaches to study and access knowledge before attending class in a way that is suitable for him. The study sample comprised 500 students diagnosed with autism who actively took part in the investigation. An initial assessment was administered to assess their current level of knowledge, following which they were randomly assigned to two groups. The control group underwent training using the Fast ForWord approach, whereas the experimental group was divided into two groups based on a pre-assessment exam. Each group was assigned an appropriate level and utilized the recommended adaptive tactics for their studies. A post-exam assessment was undertaken in various groups to evaluate the efficacy of different ways of enhancing students' performance.

The results of this research demonstrate that adaptive learning methods significantly improve academic performance, engagement, and behavior in students with ASD compared to the Fast ForWord program. Machine learning models, particularly the Gaussian Process Regressor (GPR), effectively predicted student scores and highlighted the importance of initial academic performance, engagement, and behavior in educational outcomes. These findings suggest the potential of personalized educational strategies and the integration of machine learning to improve education for students with ASD. Based on the research results, several recommendations were proposed. Future studies should explore the long-term effects of adaptive learning methods on academic performance and engagement. This includes examining how sustained use of these technologies impacts students over multiple academic years. Investigate the potential of other machine learning algorithms for predicting student scores and improving educational outcomes. Algorithms such as Random Forests, Neural Networks, and Ensemble Methods could offer additional insights and performance benefits. Conduct studies that examine the implementation of adaptive learning technologies in various educational settings, including under-resourced schools, different cultural contexts, and across various grade levels. Investigate how adaptive learning methods impact different student populations, such as those with learning disabilities, English language learners, and gifted students.

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