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PREDICTING BEHAVIOR CHANGE IN STUDENTS IN SPECIAL EDUCATION

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ABSTRACT

Students with special educational needs (SEN) often face difficulties that include hyperactivity, short attention span, and emotional instability, which can impact their academic, social, and personal growth. Applied Behavior Analysis (ABA) is an evidence-based intervention that uses the principles of reinforcement and stimulus control to promote desirable behavioral outcomes. While ABA interventions are systematic and based on empirical evidence, very little research has been conducted on predicting behavior change through advanced data-driven methodologies.

This study seeks to improve the ABA practice through a multimodal learning analytics, MMLA, as well as machine learning (ML) technique for the purpose of predicting behavior change among SEN students. The work developed a multimodal data collection system that gathers data from 1,130 sessions of ABA therapy comprising ambient, physiological, as well as motion data, and statistical analysis shows sensor and wearable data significantly improve accuracy in comparison to traditional educational data. Furthermore, ML models including DNN effectively predict changes in behavior with performance benchmarking of effectiveness against related works. This research brings new insights to ABA practices in integrating IoT technologies and advanced analytics into behavioral interventions. The results have practical implications for the improvement of student outcomes in SEN and open a ground for future work on MMLA's application in special education.

Keywords-Special Education Needs (SEN), Applied Behavior Analysis (ABA), Behavior Change Prediction, Multimodal Learning Analytics (MMLA), Machine Learning (ML), Deep Neural Networks.

I. INTRODUCTION

Students with special educational needs often face problems like hyperactivity, inability to concentrate, and emotional instability, which affect their academic progress and social interaction. Disorders like autism spectrum disorders are linked to the anomalies in the development of the brain, whereas attention deficit hyperactivity disorder and several learning disabilities are due to genetic factors. These challenges may, at times, lead to such behavior as aggression or self-mutilation, which also inhibits the development and learning of a student. Hence, encouraging positive behavior is the most important goal in teaching students with SEN.

Applied Behavior Analysis is one of the most powerful and well-established methods in behavior enhancement for students with SEN. This approach is known for its emphasis on the reinforcement of positive behaviors and new skill instruction, utilizing such techniques as reward systems and explicit instructions. Despite all these advancements achieved in ABA techniques, such as tools for data tracking and provision of real-time feedback, a deficiency still exists regarding research on the prediction of behavior changes in the course of therapy.

This gap is an area where learning analytics can be of great importance. Learning analytics is a methodology that uses data to gain insights into and enhance the learning process, and it is being used extensively in educational contexts currently. The integration of Applied Behavior Analysis with learning analytics makes it possible not only to monitor a student's behavior more effectively but also to predict how it may evolve, thereby improving therapy strategies and outcomes.

This study aims to fill that gap by predicting how the behaviors of students with SEN evolve during ABA therapy using multimodal learning analytics. The research explores patterns in data collected from sessions of therapy, evaluates whether wearable sensors can add to insights, and compares performance of machine learning algorithms in predicting behavior against traditional approaches.

This research is capable of making Applied Behavior Analysis (ABA) therapy for students with Special Educational Needs (SEN) more effective and personalized in the achievement of these objectives. It may facilitate their academic and social development. The results will provide great insights that may not only benefit the special education domain but also the wider community engaged in supporting students with distinctive learning requirements.

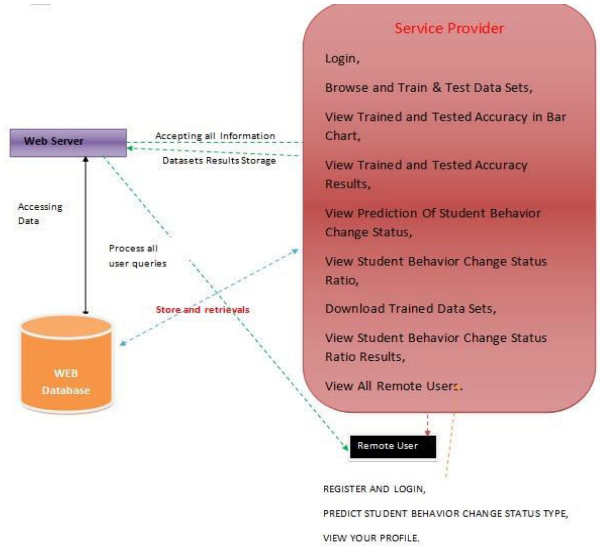

Fig 1: System Architecture

II. RELATED WORK

Favorable traits of physical learning environment at preschool level for slow learners

Authors: S. S. Ahmad, M. F. Shaari, R. Hashim, and S. Kariminia (2015)

This study examines the critical characteristics of physical learning environments that positively affect slow learners in preschool settings. The research involved factors such as lighting, spatial arrangement, and classroom design, which were found to contribute to better learning outcomes among children with special educational needs. The authors emphasize the role of a sensory-friendly and well-organized environment in improving attention and engagement for slow learners.

Investigating the effects of the lighting and acoustic environments on the learning development of children with cognitive disabilities in special education in UAE

Author: M. M. Karima(2017)

Karima's thesis researches how factors of lighting and acoustics influence the development of children with cognitive disabilities in special educational settings within the UAE. The findings of the research revealed that proper lighting and acoustic conditions may enhance cognitive development and lower stress levels, which greatly benefit the children with special educational needs. The study shows how environmental factors play a key role in supporting the learning process of children with cognitive challenges.

Accelerated Learning in the Classroom

Author: A. Smith (1996)

Smith's book deals with accelerated learning techniques in the classroom, discussing how educators can apply certain strategies to enhance the learning experience. While not directly aimed at special education, the techniques presented here can be adapted for special educational needs, especially for accelerating learning and enhancing participation through effective teaching and environmental modifications.

Influence of background music on behavior and physiological responses of special educational needs children: An exploration

Author: A. Savan (1998)

This research investigates how background music affects children with special educational needs, mainly on behavior and physiological responses. The findings of this study imply that music can be very soothing and enhance concentration as well as emotional control in the lives of children with special needs. The result is crucial for preparing therapeutic and supportive learning environments for the children with behavioral or emotional challenges.

Patterns of skin conductance in learning disabled students

Author: G. B. Werbach (1979)

Werbach's PhD thesis on the physiological response, especially the skin conductance, to learning disabled students. In this study, it was identified how the emotional and cognitive responses in the children with learning disabilities might be measured, giving great insight to their ability to regulate emotionally and the nature of the stress they undergo. These results conclude that physiological assessment may help to assess the behavioral requirements of students and support special educational needs.

Moving bodies to moving minds: An exploration of the use of motion-based games in special education

Authors: P. Kosmas, A. Ioannou, and S. Retalis(2018)

This study discusses the application of motion-based games in special education. The authors conclude that these games are very effective in enhancing both physical and cognitive skills, leading to better engagement and learning

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outcomes. Motion-based games integrate physical movement with learning tasks, which helps children with special educational needs, such as autism or ADHD, to focus, learn, and interact with their environment.

III. IMPLEMENTATION

The implementation phase of software development is the crucial stage when the design is finally converted into a fully functional system. This involves setting up necessary software and hardware environments, and then configuring servers, databases, and development tools in a correct manner. Starting from there, developers implement the software as soon as the environment is prepared with respect to design guidelines and coding standards. Unit testing is a method where every module, which represents a specific functionality, is developed and tested independently. All the modules are then integrated together to form the complete system and integration testing is performed to ensure that all the parts work well together. Subsequently, the user interface is designed to be user-friendly and intuitive and is properly tested to ensure usability. User acceptance testing and all other forms of system-wide testing should be conducted to ensure that the system achieves user and technical requirements. After that, the system is tuned for performance, and then flaws detected are corrected. Documentation produced includes technical guide for developers and user manuals to ensure the developers and even the end users can apply and maintain the system efficaciously. Then, the system is deployed and if required, data migration is taken care of properly. After deployment, the system is continuously maintained and monitored to take care of any problems. This stage ensures that the system is successfully deployed, thoroughly tested, and supported for future enhancements.

IV. ALGORITHM

Decision Tree Classifier

Decision Tree Classifier is a very strong classifier. It creates a tree-like model in which each internal node represents an attribute test (or decision) and each leaf node represents a class label. The algorithm starts with the selection of the most informative attributes according to some criteria (for example, information gain), and then recursively builds a tree for each partition. This method is rather simple and easy to interpret, thereby making it very effective for any task where the decision path needs to be understood.

Gradient Boosting

This technique forms ensembles by building models incrementally, and it uses boosting algorithms usually taking some error, typically from a weak decision tree learner. This kind of model is quite capable and robust in dealing both with regression and classification-type tasks. Gradient boosted trees usually outperform other ensembles like random forests at least in terms of minimalizing the loss.

K-Nearest Neighbors (KNN)

The KNN is a simple non-parametric classification algorithm based on the majority vote of its nearest neighbors. A method is "lazy" as it does not have to learn a model when training but makes predictions with test instances compared to the training data in the testing phase. The secret sauce is to measure

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similarity in a distance metric (Euclidean, for example).

Logistic Regression Classifier

Logistic regression is applied for binomial and multinomial classification. It describes the relationship between independent variables and a categorical dependent variable. The algorithm calculates probabilities by applying a logistic function to create odds ratios for each predictor. Logistic regression does not assume normality of the predictors, hence more versatile than discriminant analysis, especially if the objective is to model a binary outcome.

Naive Bayes

The Naive Bayes classifier is based on Bayes' Theorem, which assumes independence between features. It works well in practice, especially in text classification and other areas where features are conditionally independent. It is fast and efficient, and works well even on large datasets.

Random Forest

Random Forest is an ensemble technique that builds many decision trees and combines their output. Every tree is trained on a randomly selected subset of the data, and the final prediction is done by averaging the outputs (for regression) or by taking the majority vote (for classification). This reduces overfitting and provides a more robust model compared to a single decision tree.

Support Vector Machine (SVM)

It has the ability to create very efficient classifiers by finding the separating hyper-plane within any multidimensional space that best classifies the different classes present therein. SVM maximizes inter-class distance, and a larger distance between the different classes increases the model generalization capability. It finds high performance in spaces, even when the dimensions overwhelm the number of samples to be taken.

RESULT

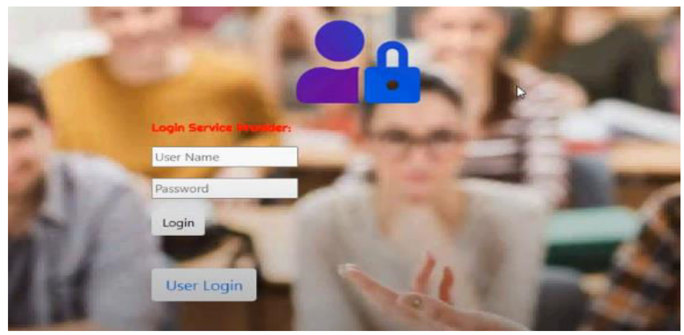

Fig:1: User Login

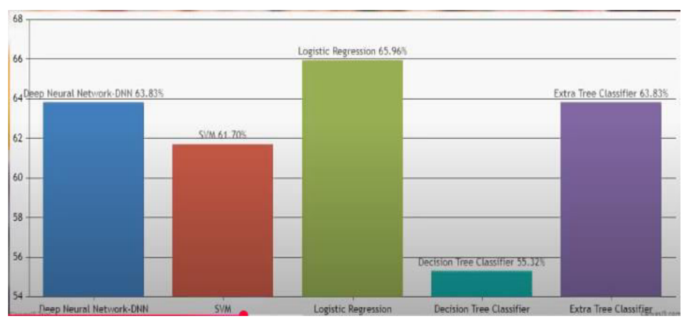

Fig:2:Algorithms Accuracy

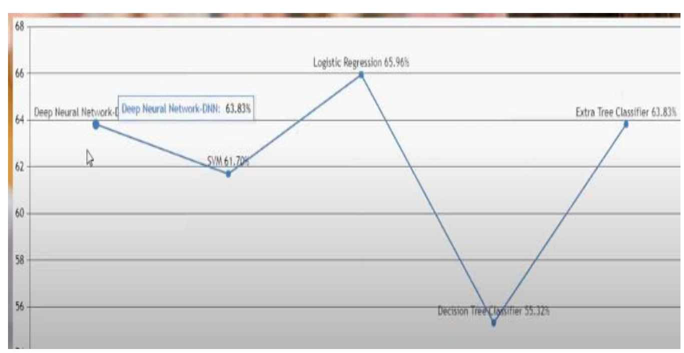

Fig:3:Accuracy Results

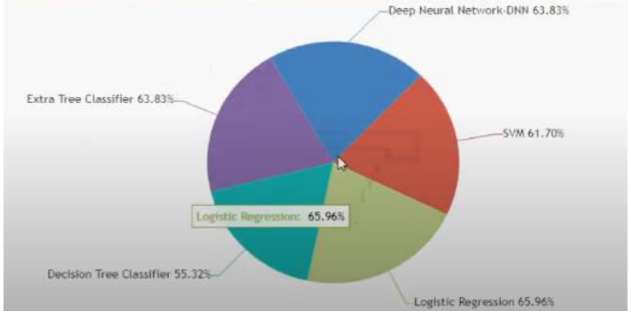

Fig:4:Pie chart Accuracy Results

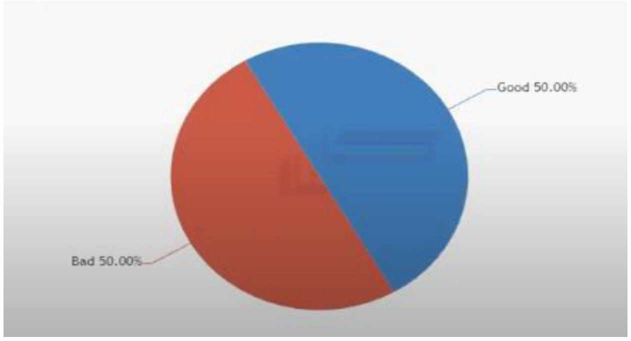

Fig:5:Student Behaviour

CONCLUSION

This research looks into the use of MMLA in predicting behavioral change for students with special educational needs that are under applied behavior analysis treatment. Data from IoT sensors, including environmental factors, physiological measurements, and movement data, are also incorporated to build statistical models that would better predict such behavioral change among students with SEN. The ML and deep learning techniques were applied, optimized, and evaluated to demonstrate their feasibility in achieving better predictive abilities for change outcomes in behavioral performance during ABA therapy.

There was multicollinearity in most of the variables; however, the regression analysis was still applied without issue. More important, data from both sensor and wearable sensors led to significant gains in predicting behavior change better. The results indicated that ML, and particularly deep learning, may be used to successfully supplement MMLA in order to predict outcomes in SEN students treated with ABA therapy. The performance of the models developed within the scope of this study exceeded most of the existing approaches within MMLA, with some variability in the predictions across models.

ABA therapy is an effective intervention that would contribute to the behavioral change for the personal and social development of SEN students, in addition to promoting positive behaviors in SEN students. The importance of the learning environment and physiological states during therapy sessions is highlighted in this study as playing a significant role in the acquisition of behavioral skills and subsequent behavior change. Although the results look promising, the study also points out some limitations and areas for future research. Altogether, this study contributes to an increasing use of machine learning in educational settings for students with developmental and brain disorders and can provide insights that may help optimize ABA therapy interventions.

REFERENCES

[1] S. S. Ahmad, M. F. Shaari, R. Hashim, and S. Kariminia, ''Conducive attributes of physical learning environment at preschool level for slow learners,'' Proc.-Social Behav. Sci., vol. 201, pp. 110–120, Aug. 2015.

[2] M. M. Karima, ''Evaluating impact of the lighting and acoustic environments on the learning development of children with cognitive disabilities in special education in UAE,'' M.S. thesis, Fac. Eng. IT, British Univ. Dubai, Dubai, UAE, 2017.

[3] A. Smith, Accelerated Learning in the Classroom. Stafford, U.K.: Network Continuum Education, 1996.

[4] A. Savan, ‘‘A study of the effect of background music on the behaviour and physiological responses of children with special educational needs,’’Psychol. Educ. Rev., vol. 22, pp. 32–36, Feb. 1998.

[5] G. B. Werbach, ‘‘Skin conductance patterns among learning disabled students,’’ Ph.D. dissertation, Dept. Special Educ., California State Univ.,Fresno, CA, USA, 1979.

[6] P. Kosmas, A. Ioannou, and S. Retalis, ‘‘Moving bodies to moving minds: A study of the use of motion-based games in special education,’’ TechTrends, vol. 62, no. 6, pp. 594–601, Nov. 2018.

[7] P. Blikstein and M. Worsley, ‘‘Multimodal learning analytics and education data mining: Using computational technologies to measure complex learning tasks,’’ J. Learn. Anal., vol. 3, no. 2, pp. 220–238, Sep. 2016.

[8] X. Ochoa and M. Worsley, ‘‘Augmenting learning analytics with multimodal sensory data,’’ J. Learn. Anal., vol. 3, no. 2, pp. 213–219, Sep. 2016.

[9] D. Di Mitri, J. Schneider, M. Specht, and H. Drachsler, ‘‘From signals to knowledge: A conceptual model for multimodal learning analytics,’’J. Comput. Assist. Learn., vol. 34, no. 4,pp. 338–349, Aug. 2018.

[10] M. Kourakli, I. Altanis, S. Retalis, M. Boloudakis, D. Zbainos, and K. Antonopoulou, ‘‘Towards the improvement of the cognitive, motoric and academic skills of students with special educational needs using Kinect learning games,’’ Int. J. Child-Comput. Interact., vol. 11, pp. 28–39,
Jan. 2017.

[11] P. Kosmas, A. Ioannou, and S. Retalis, ‘‘Using embodied learning technology to advance motor performance of children with special educational needs and motor impairments,’’ in Proc. Eur. Conf. Technol. Enhanced Learn., 2017, pp. 111–124.

[12] O. Rudovic, J. Lee, M. Dai, B. Schuller, and R.W. Picard, ‘‘Personalized machine learning for robot perception of affect and engagement in autism
therapy,’’ Sci. Robot., vol. 3, no. 19, Jun. 2018, Art. no. eaao6760.

[13] M. S. Goodwin, C. A. Mazefsky, S. Ioannidis, D. Erdogmus, and M. Siegel,‘‘Predicting aggression to others in youth with autism using a wearable biosensor,’’ Autism Res., vol. 12, no. 8, pp. 1286
1296, Aug. 2019.

[14] P. A. Alberto and A. C. Troutman, Applied Behavior Analysis for Teachers, 9th ed. Upper Saddle River, NJ, USA: Pearson, 2013.

[15] B. S. Abrahams and D. H. Geschwind, ‘‘Advances in autism genetics:On the threshold of a new neurobiology,’’ Nature Rev. Genet., vol. 9, no. 5,pp. 341–355, May 2008.

[16] L. Bassarath, ‘‘Conduct disorder:A biophysical review,’’ Can. J. Psychiatry,vol. 46, no. 7, pp. 609–617, 2001.

[17] J. O. Cooper, T. E. Heron, and W. L. Heward, Applied Behavior Analysis,3rd ed. Hoboken, NJ, USA: Pearson, 2020.

[18] R. Pennington, ‘‘Applied behavior analysis: A valuable partner in special education,’’ Teach. Except. Child., vol. 54, no. 4, pp. 315–317, 2022.

[19] F. J. Alves, E. A. De Carvalho, J. Aguilar, L. L. De Brito, and G. S. Bastos,

‘‘Applied behavior analysis for the treatment of autism: A systematic review of assistive technologies,’’ IEEE Access, vol. 8, pp. 118664–118672, 2020.
[20] M. C. Buzzi, M. Buzzi, B. Rapisarda, C. Senette, and M. Tesconi, ‘‘Teaching low-functioning autistic children: ABCD SW,’’ inProc. Eur. Conf. Technol. Enhanced Learn. Berlin, Germany: Springer, 2013, pp. 43–56.
[21] V. Bartalesi, M. C. Buzzi, M. Buzzi, B. Leporini, and C. Senette, ‘‘An analytic tool for assessing learning in children with autism,’’ in Universal Access in Human-Computer Interaction, Universal Access to Information and Knowledge, vol. 8514, C. Stephanidis and M. Antona, Eds. Cham, Switzerland: Springer, 2014.
[22] G. Presti, M. Scagnelli, M. Lombardo, M. Pozzi, and P. Moderato,‘‘SMART SPACES: A backbone to manage ABA intervention in autism across settings and digital learning platforms,’’ in Proc. AIP Conf.,vol. 2040, 2018, Art. no. 140002.
[23] G. Siemens and R. S. J. D. Baker, ‘‘Learning analytics and educational data mining: Towards communication and collaboration,’’ in Proc. 2nd Int.
Conf. Learn. Analytics Knowl., Apr. 2012, pp. 252–254.
[24]D. M. Baer, M. M. Wolf, and T. Risley, ‘‘Current dimensions of applied experimental analysis of behavior,’’ J. Appl. Behav. Anal., vol. 1,
pp. 91–97, Jan. 1968.
[25] S. Vilcekova, L. Meciarova, E. K. Burdova, J. Katunska, D. Kosicanova, and S. Doroudiani, ‘‘Indoor environmental quality of classrooms and occupants’ comfort in a special education school in Slovak Republic,’’ Building Environ., vol. 120, pp. 29–40, Aug. 2017.