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PREDICTING BEHAVIOUR CHANGE IN STUDENTS WITH SPECIAL EDUCATION NEEDS USING MULTIMODEL LEARNING ANALYTICS

Mr. S. Sathish Kumar
Assistant Professor, Department of Artificial Intelligence and Machine Learning,
J.B. Institute of Engineering and Technology, Hyderabad, Telangana, India

K. Pravardhan, E. Ajith kumar, J. Vignesh nayak, K. Narasimha
Students, Department of Artificial Intelligence and Machine Learning,
J.B. Institute of Engineering and Technology, Hyderabad, Telangana, India

ABSTRACT
The presence of educational data in new forms and modes presents new possibilities to students with special education needs (SEN), whose learning and behavior are extremely sensitive to their body states and learning environments. Multimodal learning analytics (MMLA) records learner and learning environment data in different modalities and processes them to reveal the underlying educational insights. In this paper, we used MMLA in order to forecast the behavior change of SEN students after enrolling in applied behavior analysis (ABA) therapies, in which ABA therapy is a special education intervention that seeks to treat behavioral disorders and develop positive alterations in behavior. Here we demonstrate that by feeding multimodal educational data, our deep neural network and machine learning models are able to predict SEN students' behavior change with optimal performance of 98% accuracy and 97% precision. We also illustrate how environmental, psychological, and motion sensor data can greatly enhance the statistical performance of predictive models with only conventional educational data. Our research has been utilized in the Integrated Intelligent Intervention Learning (3I Learning) System, augmenting intensive ABA therapies for more than 500 SEN students in Hong Kong and Singapore since 2020.

1. INTRODUCTION

SEN students may be observed to have certain behavioral traits like hyperactivity, short attention span, and emotional liability. Most of them are also at risk of developing neurodevelopmental and social issues [1]. Inappropriate SEN student behavior, such as that of students with autism spectrum disorders (ASD), has been linked to abnormalities in brain development [2]. In addition, attention deficit hyperactivity disorder (ADHD) and certain learning disabilities also share their genetic cause [3]. Contextually inappropriate behaviors (e.g., aggression and self-mutilation) may discourage SEN students' social and personal growth. Thus, reinforcing positive behaviors is a significant learning outcome in special education. Applied behavior analysis (ABA) therapy is an intervention method targeting SEN students' behavior modification [4]. ABA interventions are planned using the behavioral science and principles of reinforcement and stimulus control. Through the encouragement of desirable behavior modification, socially relevant outcomes can be promoted [5]. Just recently, Alves et al. presented a systematic review of ABA technologies [6], such as support systems for ABA applications (p.118667). The works that were reviewed varied from web-based services and data visualization to instructing children with low-functioning autism [7] to real-time monitoring [8] and data management [9] for individualized intervention. A lack of works addressing ABA outcomes prediction is, however, evident. Worth mentioning is that the behavior analysis processes involved in ABA therapy are evidence-based and very systematic. Such a nature makes data-driven approaches such as learning analytics (LA) appropriate for advancing ABA-related technologies. In contrast, LA is frequently used in educational practice to comprehend and maximize learning and the learning environment [10], which renders it capable of maximizing current ABA practice.

2. LITERATURE SURVEY

The use of Multimodal Learning Analytics (MMLA) in the analysis and prediction of student behavior has increased immensely, particularly among students with special education needs (SEN). The conventional method has been limited in capturing the complexity of learning behaviors owing to the narrow sources of data

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and the staticity of instruments for assessment. This has initiated the move towards multimodal and dynamic approaches.

1. Behavior Prediction in Educational Settings: Previous research in learning analytics primarily dealt with behavioral prediction with single-modal data like log records, clickstreams, or assessment scores. The approaches gave a very limited perspective of students' learning processes. For instance, metrics such as attendance or scores on tests were widely employed, which did not capture the learner's engagement or cognitive states entirely.

2. Emergence of Multimodal Learning Analytics: MMLA combines heterogeneous streams of data—video, audio, physiological sensors, and interaction logs—to build a more comprehensive view of student behavior. Experiments have shown that integrating multiple data sources can produce more accurate and richer models of learner engagement and emotional states. This is especially relevant for SEN students, whose learning patterns may not be amenable to traditional metrics.

3. SEN and Behavioral Interventions Studies: Multiple analyses have used analytics and AI-powered models to help SEN groups, particularly those that have autism, ADHD, or emotional and behavioral disorders. They tend to offer real-time feedback mechanisms, custom learning trajectories, and behavior classification algorithms. Much of these investigations, however, did not predict but rather applied retrospective analysis.

4. Predictive Modeling and Temporal Analysis: Recent literature has shown a growing interest in temporal modeling techniques like Long Short-Term Memory (LSTM) networks and Hidden Markov Models (HMMs), which can capture the evolving nature of student behavior. These models are capable of identifying transitions in affective and cognitive states over time, allowing for the anticipation of problematic behavior and timely intervention.

5. Challenges in MMLA for SEN: While promising, difficulties remain, including the requirement of high-quality labeled data, issues of privacy, and fusion of different data modalities. In addition, how to make predictive models interpretable and usable by instructors is an ongoing issue in the area.

METHODOLOGY

Given the annotated samples resulting from the data preprocessing stage, we carry out standard ML procedures, such as class balancing, training, cross-validation, and testing, to produce our predictive model.

1) DATA PROCESSING PIPELINE

The data pipeline of our ML procedures is presented in Fig. 7.Firstly, we divide our samples (N = 1,130) into training and test sets in an 80% to 20% ratio. The test samples (n = 226) are held out and used exclusively for the testing phase. Various resampling methods are then applied to the training set (n = 904). Validation sets have been randomly extracted from the resampled training set to assess the training model’s convergence. Lastly, the held-out training samples are used to evaluate the optimised model.We evaluate all trained models with metrics, including accuracy, precision, recall, and F-1 scores. The most optimum predictive model for the data is selected.

2) RESAMPLING AND CLASS BALANCING

Uneven class balance is a frequent problem in real-world ML practice. Prior to our ML modelling process, we examine our statistical analysis result to detect any uneven class balance within our dataset. We then apply any necessary data augmentation techniques to enhance the class balance of our training data. We use APIs from the Python imbalanced-learn toolbox to perform data resampling. The imbalanced classes problem exists in our annotated samples, where the size of negative and positive samples are $n0 = 951$ and $n1 = 179$, respectively. Therefore, we apply those standard resampling methods and algorithms listed in Table 2 to augment our training dataset.

3) ML MODELS BUILDING AND EVALUATION

We employed a range of well-established classifiers to construct the predictive models. Specifically, we used the k-nearest neighbours (kNN), decision tree (DT), random forest(RF), Naive Bayes classifier (NBC), multi-layer perceptrons(MLP), support vector machine (SVM), and XGBoost algorithms to build these classifiers. In addition, we also utilised a deep neural network (DNN) as a more advanced ML technique for classification. To ensure that our models were reliable and accurate, we followed rigorous training, validation, and testing procedures in standard ML practice. We used the data pipeline described in Fig. 7 to split the data into training and testing sets. The training set was used to train the classifier models, while the validation set was used to tune their hyperparameters and prevent overfitting. Finally, the testing set was used to evaluate the performance of the

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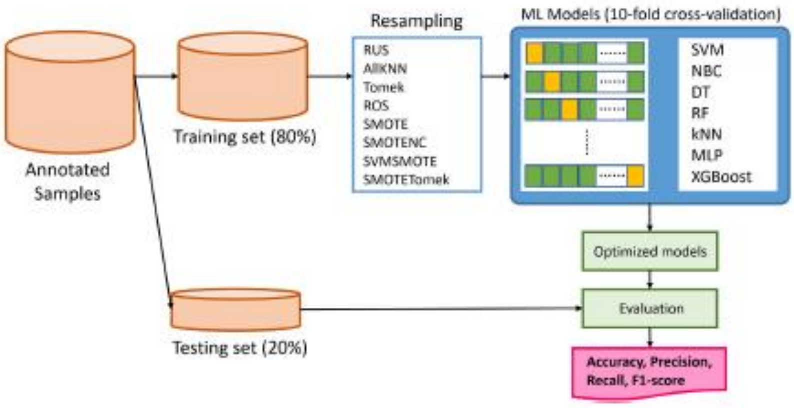
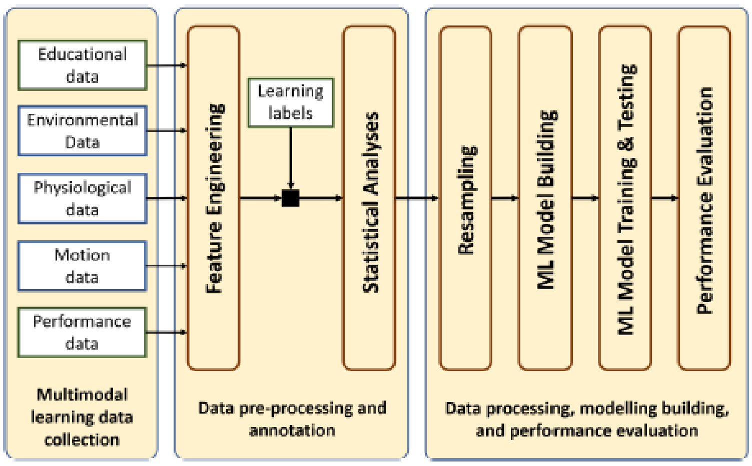
models on unseen data. This approach allowed us to identify the most suitable ML algorithm for our specific problem and to optimise its performance through careful hyperparameter tuning.



Data pipeline of the current study



The overall workflow

APPLICATIONS

The application of multimodal learning analytics (MMLA) in predicting behaviour change among students with Special Education Needs (SEN) holds immense potential across educational, therapeutic, and administrative domains. One of the primary applications is in early intervention, where predictive models can identify signs of emotional distress, disengagement, or disruptive behaviour before they escalate, allowing educators and support staff to respond proactively. By integrating data from various sources—such as facial expressions, speech patterns, body movements, academic performance, and physiological signals—MMLA can provide a richer understanding of a student's emotional and cognitive state in real time. This enables the creation of personalized learning environments, where teaching methods, content delivery, and classroom settings are adapted to meet the specific needs of each student. In addition, such systems can assist special educators and therapists by offering objective insights into behavioural patterns over time, supporting individualized education plans (IEPs) with data-driven evidence. On an administrative level, schools can use these insights to allocate resources more effectively, identify common challenges among student populations, and develop policies that promote inclusive education. Furthermore, these predictive systems can be integrated into digital learning platforms, enabling remote monitoring and support for SEN students in hybrid or online learning environments. Ultimately, the project contributes to building more empathetic, responsive, and effective educational systems that empower students with special needs to reach their full potential.

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CONCLUSION

We applied MMLA to predict behaviour change in SEN students participating in ABA therapies. A novel MMLA approach for the prediction of SEN students behaviour change achievement in ABA therapy is presented. We introduced IoT sensors data, including ambient environmental measurements (namely CO2 level, humidity, light intensity, and temperature), physiological measurements (namely IBI, BVP, GSR, and skin temperature), and motion measurements (accelerometer values in X, Y, and Z directions) to develop statistical models for ABA therapy.We also apply ML and DNN techniques to predict SEN students' behaviour change.We studied the statistical characteristics of the multimodal educational data and found that most of our data are not normally distributed. Significant correlations between the variables had been identified, but the problem of multicollinearity did not exist in our variables. We further showed that sensors and wearable data could significantly enhance the prediction of SEN students' behaviour change achievement. Various ML algorithms and a DNN were built, optimised, and evaluated. Our results demonstrated that ML(including deep learning) could be applied to MMLA for predicting SEN students' behaviour change. While the performance of our classifiers and DNN surpass most of the existing MMLA models. However, we also observed variations in the prediction targets among the compared models. Promoting positive behaviours in SEN students is important for their personal and social development. At the same time, ABA therapy is an effective intervention approach that aims at behaviour change in this population group. The learning environment and the learner physiology conditions during ABA therapy sessions are essential for understanding behaviour skills acquisition and their effect on subsequent behaviour change. The current study has affirmed the predictive relations between the learning environment, learner physiology, and the learning outcome in ABA therapy. A number of limitations and necessary future works are also presented. Overall, our work echoes the growing demands in applying ML to the learning and education of those with brain and developmental disorders.

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