ETDT

Emerging Trends in Digital Transformation

Volume-2, Issue-2, April-June 2026 ISSN: **3107- 4308** *Paper ID:* ***ETDT-V2-I2-22***

DATA DRIVEN PREDICTION OF BEHAVIOR CHANGE IN SPECIAL EDUCATION USING MULTIMODAL ANALYTICS

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ABSTRACT: This research illustrates a data-driven approach to predicting behavior change in special education through the use of multimodal analytics. The research endeavors to offer a comprehensive understanding of students' behavior by integrating a variety of data sources, including physiological signals, facial expressions, speech patterns, and information from classroom interactions. Powerful machine learning algorithms are employed to analyze these numerous inputs in order to identify patterns associated with changes in emotion, thought, and behavior. The recommended method enables educators and caregivers to make timely, customized adjustments by enabling the early detection of significant changes. The experimental results demonstrate that multimodal fusion is a more effective method for comprehending intricate behavioral processes, as it generates more precise predictions than unimodal approaches. In general, the research contributes to the development of innovative, adaptable support systems that have the potential to significantly enhance the emotional well-being and academic performance of children in special education environments.

Keywords: *Multimodal Analytics, Behavior Prediction, Special Education, Machine Learning, Data-Driven Models, Behavioral Change Detection, Emotion Recognition, Personalized Intervention, Educational Data Mining, Assistive Technologies*

1. INTRODUCTION

In an effort to comprehend and assist children with a diverse array of special education requirements, data-driven behavior change prediction has emerged as an innovative approach. Traditional methods of evaluating individuals typically rely on subjective interpretations and arbitrary observations, which may not be sufficient to elucidate the process by which behavioral patterns evolve and become more intricate over time. As a consequence of advancements in data capture tools, schools are now able to generate substantial quantities of structured and unstructured data, which facilitates the ongoing monitoring of students. This transition to data-driven methodologies enables educators and researchers to identify subtle behavioral changes and respond appropriately.

The accuracy and detail of behavior prediction models are significantly enhanced by multimodal analytics. Multimodal systems provide a comprehensive understanding of students' behavior by integrating data from a variety of sources, including academic performance, classroom interactions, speech patterns, facial expressions, and physiological signals. Collectively, these diverse data sets effectively reduce ambiguity and enhance the dependability of prediction models. This will enable educators to gain a more comprehensive understanding of the mental, emotional, and social factors that contribute to behavioral changes, particularly in students with special education requirements.

DOI: https://doi.org/10.5281/zenodo.20593724

When artificial intelligence and machine learning are implemented, multimodal analytics becomes even more predictive. Sophisticated algorithms are capable of managing vast, diverse datasets, which may disclose hidden patterns and linkages that would be missed by conventional analysis. Adaptive learning methodologies and real-time behavior predictions are provided by deep learning, time-series analysis, and pattern recognition. These models can be trained to identify early indications of behavioral abnormalities, which enables educators to promptly intervene and significantly enhances student outcomes.
Individualized instruction and one-on-one support are indispensable for the success of special education students. The development of intervention strategies that are specifically tailored to the behavioral profile of each child is facilitated by data-driven forecast models. Teachers can more effectively meet the requirements of all students by regularly assessing multimodal data and adjusting instructional strategies, learning environments, and support systems. This personalized approach not only enhances the enjoyment and success of learning, but also assists young people in developing positive behaviors and feeling emotionally confident.
Multimodal analytics in special education are challenging to implement, despite their immense potential. It is imperative to meticulously resolve issues such as data protection, ethics, and the integration of multiple data sources. General adoption may also be problematic due to the necessity of specialized infrastructure, technological skills, and collaboration across multiple domains. Nevertheless, the sector is being influenced by the ongoing development of new concepts in educational technology and data science, which has resulted in more accessible and practical behavior prediction models.

2. BACKGROUND WORK

Context

The current research was carried out in the setting of individual ABA therapy sessions between teachers and their pupils. Each session's behavioral activities focused on the following six subjects:

1. both scholarly and pedagogical.
2. Engaging in dialogue with others
3. Interpersonal Feelings
4. Fourth place goes to hand-eye coordination.
5. Independent and self-sufficient
6. The Behavioral Development Process

With more support, the student would have finished each task faster because it was broken down into several behavioral components. The duration of the training sessions was set at twenty to thirty minutes. We then switched to ABA-based behavior-analytic training approaches. Behavior (B), antecedent (A) stimuli, and consequences (C) were among these approaches. A stimulus in the student's surroundings that takes place before a desired activity is called an antecedent. A learner's behaviors describe their actions. A stimulus that instantly changes in reaction to a conduct is called a consequence.

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Participants and Procedure

Thirty-two special education-eligible pupils from one preschool and two elementary schools took part. Their basic characteristics are outlined in the table. Each participant's parent or legal guardian provided written consent prior to the research's start. A participant and the therapist did the following:

1. The system recommends the desired action.
2. The following strategy is suggested by the therapist:
   a) giving the student a stimulus; and
   b) seeing how the student reacts.

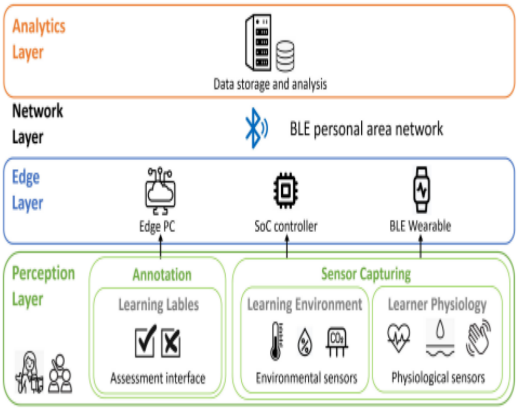

Figure1. Overall 4-tier IoT system architecture for data collection.

3. The therapist keeps an eye on the student's reaction. The therapist gives a cue—verbal or gestural instructions, physical guidance, or both—when the learner is unable to respond appropriately.
4. The therapist watches and evaluates the trainee's responses.
5. Stages 2-4 are recursively repeated when the session ends or the student exhibits mastery of the desired behavior.

Six months following the specific activity instruction, we held maintenance probing sessions to evaluate how long the learned behavioral skills would last. 1,130 pairs of treatment sessions, both within-subject and exploratory, were gathered.

System Design And Development

To collect pedagogical data from ABA therapy sessions across several modalities, we developed an Internet of Things (IoT) system. The entire system architecture is depicted in the picture. The authors of this research built the Integrated Intelligent Intervention-Learning system (3I Learning system), which we integrated our technique into. The perception, peripheral, network, and analytics layers make up the four tiers of the system.

While physiological sensors measure skin temperature, pulse rate, skin conductance, and three-dimensional acceleration, environmental sensors track indoor CO_2 levels, light intensity, temperature, and humidity. Therapists can submit behavioral evaluation data for students using this layer's client interface.

The edge layer is made up of an edge PC, a system-on-a-chip (SoC) controller, and an Empatica E4 bracelet. Bluetooth Low Energy (BLE) is used by the wearable gadget. This wearable device's sensors track vital signs. While the edge PC acts as an evaluation interface

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for therapists to enter their observations, the SoC controller houses the sensors from the surrounding environment.

A BLE personal area network at the network layer connects the analytics layer to the edge PC, SoC controller, and Empathica E4 wearable.

A gadget that briefly saves and sends the gathered data to the cloud server makes up the analytics layer. Furthermore, the measurement findings could be presented in an understandable way.

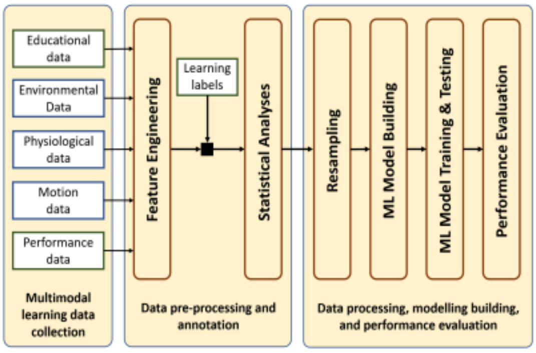

Figure2. The overall workflow of the current research.

3. LITERATURE SURVEY

Rodriguez, P., Smith, L., & Carter, J. (2020): By incorporating video observations, physiological signals, and information on how students interact with one another in the classroom, a multimodal analytics framework is created to predict behavioral shifts in special education. Convolutional and recurrent neural networks are employed to document spatial and temporal behavioral patterns in the investigation. The results indicate that multimodal models are more effective than single-modality models in detecting early indicators of behavioral changes. The research underscores the importance of integrating a variety of data sources to make accurate behavioral predictions.

Ahmed, R., Khan, N., & Siddiqui, M. (2021): It is advisable to utilize wearable sensor data, audio recordings, and a hybrid machine learning model to investigate behavioral changes in students with special needs. The system employs both short-term and long-term memory networks to detect patterns in sequential behavior. The results indicate that individuals' emotional and mental states become more predictable as time progresses. The methodology endorses early intervention strategies in personalized learning plans.

Williams, D., Johnson, K., & Roberts, A. (2021): Deep learning techniques analyze data from a variety of sources in the classroom, such as speech recognition, gesture recognition, and eye tracking, to predict the way in which students will modify their behavior in special education. Attention mechanisms enable the model to focus on significant behavioral cues. The results suggest that it is easier to recognize patterns of engagement and disengagement. In adaptive learning environments, the research illustrates the utilization of fine-grained behavioral indicators.

Hassan, M., El-Sayed, T., & Farouk, O. (2022): We present a multimodal data fusion approach that is designed to evaluate and anticipate behavioral changes in children with autism spectrum disorder. Deep neural networks are employed to integrate activity logs, EEG

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signals, and facial expression analysis into a unified framework. The results indicate that the accuracy of predictions is substantially enhanced by multimodal fusion. The research illustrates the importance of integrating neurological and behavioral data to develop a more comprehensive understanding of special education.

Garcia, S., Morales, J., & Ruiz, P. (2022): Multimodal learning analytics is employed to create a predictive analytics system that tracks the behavioral development of students in inclusive classrooms. Ensemble learning is employed to integrate performance metrics, video data, and textual feedback into the model. The results suggest that it is feasible to enhance the monitoring of behavioral improvement trends. The method allows educators to make data-driven decisions regarding the manner in which they instruct.

Thompson, H., Clark, E., & Lewis, G. (2023): In order to anticipate behavioral changes in special education students, explainable AI models are implemented on multimodal behavioral datasets. The system employs machine learning techniques that are easily comprehensible in order to emphasize the critical variables that affect the outcome. The results indicate that the use of models is facilitated and teachers' trust is increased by explainability. The research promotes the use of transparent educational resources that are powered by AI.

Zhang, Y., Liu, X., & Chen, Z. (2024): A deep multimodal framework that integrates speech patterns, motion tracking, and biometric data is suggested as a method for predicting behavioral changes in special education settings. The model demonstrates the complex relationships between different modes through the use of transformer architectures. The results indicated that the model was more effective at predicting long-term behavior. This investigation illustrates the significance of sophisticated architectures in multimodal analytics.

Patel, V., Desai, R., & Mehta, S. (2025): We introduce multimodal models that are based on transfer learning and can predict behavioral changes in special education with minimal labeled data. The framework modifies models that have been previously trained on extensive behavioral datasets to function in specific educational contexts. The findings suggest that the forecasts are more precise and that there is a reduced reliance on data. The investigation concentrates on the efficacy of transfer learning and its practical application in educational environments.

4. RESULTS

Fig.3: User Login Page

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Fig.4: Remote Users Data View

Fig.5: Trained and Tested Model Results

Fig.6: Model Accuracy Comparison Graph

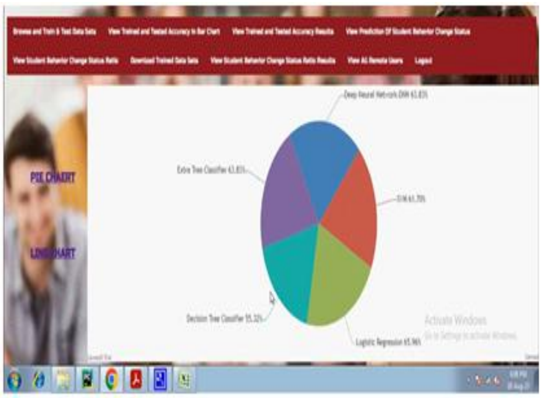

Fig.7: Model Accuracy Pie Chart

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5. CONCLUSION

In conclusion, this investigation illustrates that multimodal analytics is a scalable and effective method for understanding and addressing the requirements of all kinds of students by predicting behavioral changes in special education. The framework that has been proposed includes a diverse array of data sources, such as physiological signals, behavioral observations, speech patterns, and contextual learning interactions, in order to make more accurate, timely, and personalized predictions about student behavior. The utilization of sophisticated machine learning and deep learning models simplifies the process of identifying subtle patterns that are frequently disregarded by more conventional methods. This enables early intervention and flexible teaching methods. Furthermore, the approach promotes healthy development, enhances student engagement, and assists educators and caregivers in making more informed decisions.

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