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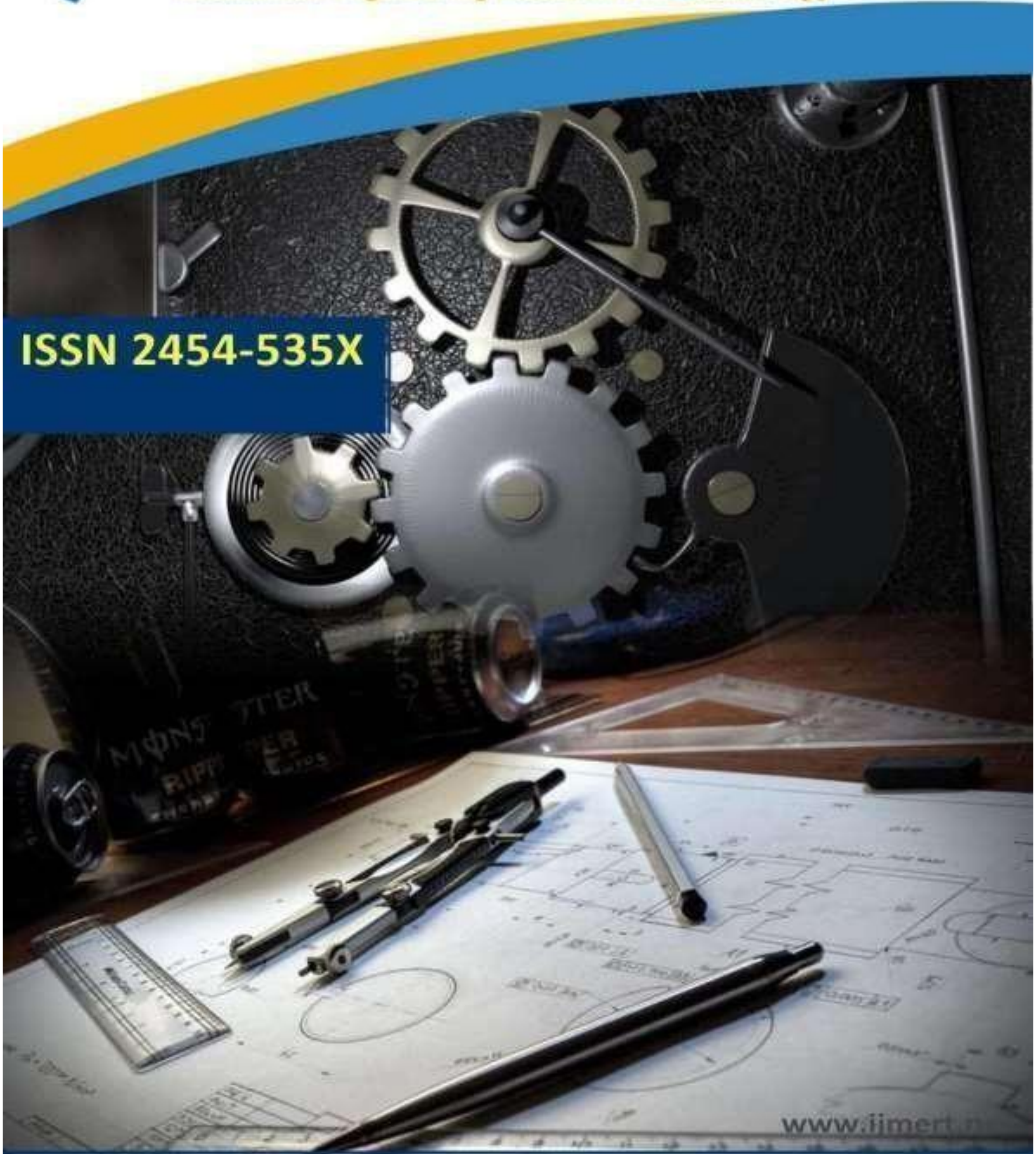

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PREDICTING BEHAVIOUR CHANGE IN STUDENTS WITH SPECIAL EDUCATION NEEDS USING MULTI MODAL LEARNING ANALAYTICS

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ABSTRACT

The availability of educational data in novel ways and formats brings new opportunities to students with special education needs (SEN), whose behavior and learning are highly sensitive to their body conditions and surrounding environments. Multimodal learning analytics (MMLA) captures learner and learning environment data in various modalities and analyses them to explain the underlying educational insights. In this work, we applied MMLA to predict SEN students' behavior change upon their participation in applied behavior analysis (ABA) therapies, where ABA therapy is an intervention in special education that aims at treating behavioral problems and fostering positive behavior changes. Here we show that by inputting multimodal educational data, our machine learning models and deep neural network can predict SEN students' behavior change with optimum performance of 98% accuracy and 97% precision. We also demonstrate how environmental, psychological, and motion sensor data can significantly improve the statistical performance of predictive models with only traditional educational data. Our work has been applied to the Integrated Intelligent Intervention Learning (3I Learning) System, enhancing intensive ABA therapies for over 500 SEN students in Hong Kong and Singapore since 2020.

I.INTRODUCTION

Students with special education needs (SEN) often exhibit behavioral Characteristics such as hyperactivity, short attention span, and emotional liability. Many are also at risk for

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academic and social problems [1]. Research suggests that inappropriate behaviors in SEN students, such as those with autism spectrum disorders (ASD), are associated with abnormalities in brain development [2]. Besides, attention deficit hyperactivity disorder (ADHD) and some learning disabilities also have their genetic origin [3]. Contextually inappropriate behaviors (such as aggression and self-harm) can hinder SEN students' social and personal development. Therefore, promoting positive behaviors is an important learning outcome in special education.

Applied behavior analysis (ABA) therapy is an intervention approach aiming at SEN students' behavior change [4]. ABA strategies are designed based on behavioral science and principles such as reinforcement and stimulus control. Through promoting desirable behavior change, socially significant outcomes can be facilitated [5]. Recently, Alves et al. offered a systematic review of ABA technologies [6], including support systems for ABA applications (p.118667). The reviewed works ranged from web-based services and data visualisation for teaching children with low-functioning autism [7] to real-time monitoring [8] and data management [9] for personalised intervention. However, a dearth of works targeting ABA outcomes prediction exists. It is worth noting that the behavior analysis processes in ABA therapy are evidence-based and highly systematic. This nature makes data-driven techniques such as learning analytics (LA) suitable for enhancing ABA-related technologies. Meanwhile, LA is often employed in educational practice to understand and optimise learning and the learning environment [10], giving it the potential to enhance existing ABA practice.

This work aims to enhance existing ABA therapy by predicting SEN students' behavior change using educational data in multiple modalities. In particular, our study is guided by the following research questions.

- **RQ1** What are the statistical characteristics of ambient environmental, physiological, and motion data collected from SEN students' ABA therapy sessions?
- **RQ2** Can sensors and wearable data enhance the prediction of SEN students'

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behavior change over traditional educational data?

• **RQ3** Can machine learning (ML) algorithms be applied to MMLA for SEN students' behavior change prediction, and what is their performance compared with other existing works in MMLA?

The above questions will be answered thoroughly in Section IV and Section V of the current paper. Our work's contributions include the following:

• We design and develop a multimodal data collection system for ABA therapies, collect and analyse data from 1,130 ABA therapy sessions, and provide detailed statistical interpretations of our results.

• We show, with statistical evidence, that sensors and wearable data can significantly enhance the prediction of SEN students' behavior change over traditional educational data.

• We demonstrate that ML algorithms and deep neural networks (DNN) can predict SEN students' behavior change accurately. We also provide extensive performance

evaluations of our predictive models and benchmark our results with other existing works.

Our research will provide new insights into ABA practices, especially in predicting students' learning with the help of the Internet of Things (IOT) sensors and wear ables. Through this work, the broad engineering community will further realize the application of MMLA to enhance behavioral interventions in SEN students and promote their skills acquisition. The new findings presented in this article also provide valuable references for future research in technologies for special education.

existing system

Applied Behavior Analysis (ABA) is an intervention method in which pedagogical strategies derived from the principles of behavior are systematically applied to promote socially significant behaviors and reduce problem behaviors [4]. The set of basic principles, which are statements about how environmental variables act as input to a function of behavior, have been evaluated scientifically by experimental analyses of behaviors (p.155). In ABA, behavior is viewed as the learner's interaction with his or her surrounding environment and involves the movement of some part(s) of the learner's body. Learning behavior occurs within the

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environmental context. At the same time, the learning environment is regarded as the full set of physical circumstances in which the learner is situated.

The learning outcome of ABA lessons is the achievement of behavior changes that improve learners' quality of life in communication and daily living skills. A systematic and measurable behavior assessment scheme is defined before the ABA lessons. The target behavior is often broken down into smaller tasks, while positive reinforcements are often used to encourage goal achievement. Assessment criteria include whether the target task is achieved (plus) or not (minus), whether a prompt from the therapist (prompt) is needed to facilitate task achievement, or if the student is behaving in a way that is unrelated to the task (off task). Furthermore, behavior change is effective if it is durable over time [11]. Therefore, a subsequent follow-up reassessment of the developed behavior is needed to ensure the effectiveness of the therapy.

Students with special needs can be susceptible to ambient environmental conditions due to their dysfunction in sensory processing. A previous study showed that high levels of CO2 content caused fatigue and difficulties in concentration in SEN students, especially those with ADHD [12]. Another study performed with intellectually disabled preschool students revealed that classroom thermal discomfort (e.g., high nearby ambient temperature) could distract them from learning and influence their mood and health [13]. The same study also suggested that students with intellectual disabilities (ID) are more vulnerable to acoustic discomforts due to their psychologically stressful conditions (p.115). Researchers also studied the relationship between classroom lighting and SEN students' comfort. They found that inappropriate lighting and glare affect individual SEN students to different extents, while they felt tired and irritated because of lighting discomfort, in general [14]. However, teachers and therapists often have no control over lighting characteristics except switching on or off (p.105).

Emotion can affect learning and engagement in students with and without SEN. In particular, students with ID often exhibit anxiety due to internal stress. Blood pressure, body temperature,

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and heart rate are physiological markers for stress that hinder learning [15]. It was shown that mild conditions could reduce these inhibitors in SEN students [16]. It is known that abnormally high or low levels of skin conductance (measured through galvanic skin response, GSR) hindered the learning performance of SEN students [17]. Besides, a study also found that body movement facilitated by motion-based technology positively impacted SEN students' short-term
memory skills.

MMLA employs multiple sources and formats of educational data such as activity logs, audio, video and biosensors to enrich learning analytics [19]. MMLA is significantly enhanced by the Internet of Things (IoT) technologies because the latter allows convenient capturing of multimodal data from the complex learning environment [20]. Multimodal educational data collected by IoT sensors include those detecting learners' motion (e.g., head and body) and physiological (e,g., heart, brain, and skin) behavior, as well as those measuring the ambient learning environment (e.g., light, humidity, temperature, and noise). These data were collected from physical objects or human bodies, then encoded into a machine-interpretable format and served as input to MMLA [21]. Possible interpretations of the observed learning process can be assigned based on validated learning theories.

Disadvantages

• Our prediction target is a binary output, which limits the available information regarding students' ABA learning for the teachers and therapists.

• The current data collection system works in a one-to-one therapist-to-student setting. While in the daily special education context, classroom teaching is often conducted in one-to-few or one-to-many manners.

• The measurement hardware in the current study is costly. For example, Empatica E4 wristbands were used, while an E4 wristband can cost more than a thousand US dollars.

II.PROPOSED SYSTEM

1) *Multimodal learning data collection:* This includes the performance of the ABA therapies and the capturing of the raw learning data arising in multiple modalities.

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2) *Data pre-processing and annotation:* This refers to extracting useful data from the raw records, producing data traces in the required modality, performing data fusion by combining the traces, and adding the learning labels to the fused data to form labeled samples.

3) *Data processing, model building and evaluation:* This consists of standard ML procedures, including any necessary resampling, model building, training, testing, and performance evaluation.

Advantages

• We design and develop a multimodal data collection system for ABA therapies, collect and analyze data from 1,130 ABA therapy sessions, and provide detailed statistical interpretations of our results. • We show, with statistical evidence, that sensors and wearable data can significantly enhance the prediction of SEN students' behavior change over traditional educational data.

• We demonstrate that ML algorithms and deep neural networks (DNN) can predict SEN students' behavior change accurately. We also provide extensive performance evaluations of our predictive models and benchmark our results with other existing works.

III.MODULES

- **Service Provider**

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Browse and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Student Behavior Change Status, View Student Behavior Change Status Ratio, Download Trained Data Sets, View Student Behavior Change Status Ratio Results, View All Remote Users.

- **View and Authorize Users**

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

- **Remote User**

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using

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authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT STUDENT BEHAVIOR CHANGE STATUS TYPE, VIEW YOUR PROFILE.

IV.CONCLUSION

In this paper, we applied MMLA to predict behavior change in SEN students participating in ABA therapies. A novel MML Aapproach for the prediction of SEN students' behavior 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' behavior 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 multi collinearity did not exist in our variables. We further showed that sensors and wearable data could significantly enhance the prediction of SEN students' behavior 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' behavior 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 behaviors 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 behavior change in this population group. The learning environment and the learner physiology conditions during ABA therapy sessions are essential for understanding behavior skills acquisition and their effect on subsequent behavior change. The current study has affirmed the predictive relations between the learning environment, learner

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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 [43].

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