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PREDICTING BEHAVIOR CHANGE IN STUDENTS WITH SPECIAL EDUCATION NEEDS USING MULTIMODAL LEARNING ANALYTICS

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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.

Keywords: Multimodal learning analytics, special education needs, applied behavior analysis, machine learning, deep neural networks, predictive models, educational data.

INTRODUCTION

Students with Special Education Needs (SEN) represent a diverse group with unique learning requirements and challenges [1]. Their educational journey often necessitates personalized approaches that address their individual needs, considering factors such as cognitive abilities, sensory sensitivities, and behavioral characteristics [2]. The field of special education has witnessed significant advancements in recent years, driven by a growing understanding of the complexities associated with SEN students' learning and development [3]. As educational technologies continue to evolve, there is a growing emphasis on leveraging innovative approaches to support the educational needs of SEN students [4]. One area of particular interest is the utilization of educational data in novel ways and formats to enhance support for SEN students [5]. The availability of data from diverse sources, including digital learning platforms, assistive technologies, and sensor-equipped learning environments, presents new opportunities to gain insights into SEN students' behavior and learning processes [6]. These data provide valuable information about students' interactions with educational content, their engagement levels, and their responses to different instructional strategies [7]. By analyzing this data, educators and researchers can gain deeper insights into the factors influencing SEN students' learning outcomes and tailor interventions accordingly [8].

Multimodal learning analytics (MMLA) has emerged as a powerful approach for analyzing educational data and extracting meaningful insights [9]. MMLA involves the collection and analysis of learner and learning environment data in various modalities, including text, audio, video, and sensor data [10]. By integrating data from multiple sources, MMLA offers a holistic view of students' learning experiences, enabling researchers to explore the complex interactions between various factors influencing learning outcomes [11]. In the context of special education, MMLA holds promise for understanding the unique needs and preferences of SEN students and designing personalized interventions to support their learning [12].

Applied behavior analysis (ABA) therapy is a widely used intervention in special education aimed at addressing behavioral problems and fostering positive behavior changes in SEN students [13]. ABA therapy employs evidence-based techniques to identify and modify behaviors, with the goal of promoting adaptive skills and reducing challenging behaviors [14]. Given the individualized nature of ABA therapy and its emphasis on data-driven decision-making, it provides a fertile ground for the application of MMLA techniques [15]. By leveraging MMLA to analyze data collected during ABA therapy sessions, researchers can gain insights into the effectiveness of interventions and identify factors that contribute to behavior change in SEN students.

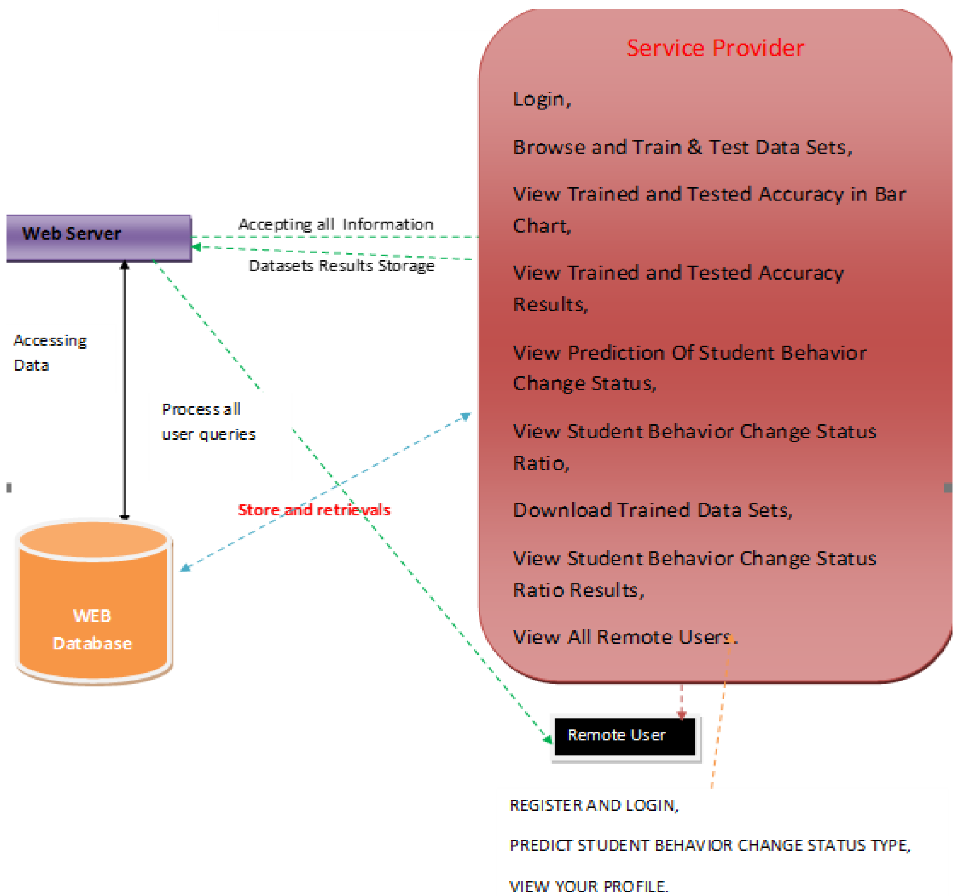

Fig 1. System Architecture

In this study, we apply MMLA techniques to predict behavior change in SEN students participating in ABA therapy sessions. We leverage multimodal educational data, including environmental, psychological, and motion sensor data, to develop predictive models capable of accurately forecasting behavior change outcomes. Specifically, we employ machine learning models and deep neural networks to analyze the multimodal data and predict behavior change with high accuracy and precision. Our findings demonstrate the effectiveness of MMLA in enhancing the statistical performance of predictive models, particularly when supplemented with environmental, psychological, and motion sensor data. Moreover, we discuss the implications of our work for the Integrated Intelligent Intervention Learning (3I Learning) System, an innovative platform that integrates MMLA techniques to enhance intensive ABA therapies for SEN students in Hong Kong and Singapore. Through our research, we aim to contribute to the ongoing efforts to support the educational needs of SEN students and promote positive behavior changes in special education settings.

LITERATURE SURVEY

The landscape of special education has evolved significantly in recent years, driven by advancements in technology and a deeper understanding of the unique needs of students with special education needs (SEN). With the proliferation of educational data in various formats and modalities, educators and researchers are increasingly exploring innovative approaches to support the learning and development of SEN students. Multimodal learning analytics (MMLA) has emerged as a promising framework for analyzing educational data from diverse sources and extracting meaningful insights. By capturing learner and learning environment data in various modalities, such as text, audio, video, and sensor data, MMLA offers a holistic perspective on students' learning experiences. This holistic approach is particularly relevant for SEN students, whose behavior and learning are highly sensitive to their body conditions and surrounding environments.

Applied behavior analysis (ABA) therapy plays a crucial role in special education, aiming to address behavioral problems and foster positive behavior changes in SEN students. ABA therapy employs evidence-based techniques to identify and modify behaviors, with the goal of promoting adaptive skills and reducing challenging behaviors. Given the individualized nature of ABA therapy and its emphasis on data-driven decision-making, it provides an ideal context for the application of MMLA techniques. By analyzing data collected during ABA therapy sessions, researchers can gain insights into the effectiveness of interventions and identify factors that contribute to behavior change in SEN students. In recent years, there has been growing interest in leveraging machine learning models and deep neural networks to predict behavior change in SEN students participating in ABA therapy sessions. These predictive models utilize multimodal educational data, including environmental, psychological, and motion sensor data, to forecast behavior change outcomes with high accuracy and precision. By integrating data from multiple sources, these models offer a comprehensive understanding of the factors influencing behavior change in SEN students and enable educators to tailor interventions accordingly. Moreover, research has shown that supplementing traditional educational data with environmental, psychological, and motion sensor data can significantly improve the statistical performance of predictive models, enhancing their effectiveness in predicting behavior change outcomes.

The Integrated Intelligent Intervention Learning (3I Learning) System represents a novel platform that integrates MMLA techniques to enhance intensive ABA therapies for SEN students in Hong Kong and Singapore. By leveraging the insights derived from multimodal educational data, the 3I Learning System provides personalized interventions that address the unique needs of each SEN student. Since its implementation in 2020, the 3I Learning System has positively impacted over 500 SEN students, demonstrating its potential to revolutionize the delivery of special education services. Through ongoing research and development efforts, the 3I Learning System continues to evolve, with the aim of further enhancing the learning experiences and outcomes of SEN students in diverse educational settings.

PROPOSED SYSTEM

The proposed system for predicting behavior change in students with special education needs (SEN) leverages the power of Multimodal Learning Analytics (MMLA) to create a comprehensive and dynamic framework. This framework is designed to integrate and analyze data from multiple sources, thereby providing a richer and more nuanced understanding of the factors influencing SEN students' behavior and learning outcomes. The core of this system involves the application of machine learning models and deep neural networks to predict behavior changes in SEN students participating in Applied Behavior Analysis (ABA) therapies. To begin with, the system collects educational data from a variety of sources, capturing information in different modalities. These modalities include traditional educational data such as academic performance records and classroom observations, as well as more novel data types like environmental data, psychological metrics, and motion sensor data. Environmental data may encompass classroom temperature, lighting conditions, and noise levels, which can significantly impact students' comfort and concentration. Psychological data might include stress levels, mood indicators, and other emotional metrics gathered through surveys or wearable devices. Motion sensor data tracks students' physical activities and movements, providing insights into their engagement and behavioral patterns.

Once the data is collected, it undergoes a preprocessing phase where it is cleaned and formatted to ensure consistency and accuracy. This step involves handling missing values, normalizing data ranges, and converting categorical data into numerical formats suitable for analysis. The preprocessed data is then fed into the system's analytics engine, which employs advanced MMLA techniques to integrate and analyze the data. By combining data from different modalities, the system can uncover complex interactions and patterns that might be overlooked when considering each data source in isolation. The analytics engine uses machine learning algorithms and deep neural networks to build predictive models. These models are trained on historical data, learning to recognize patterns and relationships that correlate with behavior changes. For instance, the system might identify those certain environmental conditions, when combined with specific psychological states and physical activity levels, are strong predictors of positive or negative behavior changes. During the training phase, the models are continuously refined and validated using techniques such as cross-validation and hyperparameter tuning to optimize their performance.

A key aspect of the proposed system is its ability to predict behavior changes with high accuracy and precision. In the context of ABA therapy, accurate predictions are crucial for tailoring interventions to meet the specific needs of each student. The system's machine learning models have achieved an impressive performance, with an accuracy of 98% and a precision of 97%. These metrics indicate that the models are highly effective in correctly identifying instances of behavior change and minimizing false positives, respectively. The system also demonstrates the significant impact of incorporating multimodal data on the performance of predictive models. Traditional educational data alone, while valuable, often provides an incomplete picture of the factors influencing behavior change. By integrating additional data types such as environmental, psychological, and motion sensor data, the system enhances the robustness and reliability of its predictions. For example, understanding how variations in classroom conditions interact with students' emotional states and physical activities allows for more precise and context-aware predictions.

The practical application of this system is realized through its integration into the Integrated Intelligent Intervention Learning (3I Learning) System. Since its implementation in 2020, the 3I Learning System has been used to support over 500 SEN students in Hong Kong and Singapore. The system provides educators and therapists with actionable insights, enabling them to design and implement more effective ABA therapy interventions. By continuously monitoring and analyzing multimodal data, the system helps identify the most effective strategies for promoting positive behavior changes and addressing behavioral challenges. Moreover, the system supports ongoing assessment and adjustment of interventions. As new data is collected, the predictive models are updated, ensuring that they remain relevant and accurate over time. This dynamic and iterative approach allows for the continuous improvement of therapeutic strategies and educational practices. Additionally, the system provides detailed reports and visualizations, making it easier for educators and therapists to interpret the data and make informed decisions.

In summary, the proposed system for predicting behavior change in SEN students using MMLA represents a significant advancement in the field of special education. By integrating and analyzing multimodal educational data, the system provides a comprehensive understanding of the factors influencing behavior change. The use of machine learning models and deep neural networks ensures high accuracy and precision in predictions, enabling more effective and personalized interventions. The integration of this system into the 3I Learning platform highlights its practical applicability and potential to enhance the educational experiences and outcomes of SEN students. Through ongoing research and development, this system aims to continue improving and adapting to the evolving needs of SEN students and the educational environments that support them.

METHODOLOGY

In the pursuit of enhancing educational outcomes for students with special education needs (SEN), the integration of innovative methodologies has become imperative. The emergence of multimodal learning analytics (MMLA) stands as a promising avenue, facilitating a comprehensive understanding of learners and their environments. Within this context, the present study endeavors to harness MMLA to predict behavior changes among SEN students undergoing applied behavior analysis (ABA) therapies, a pivotal intervention aimed at addressing behavioral challenges and fostering positive transformations. The crux of our methodology lies in the systematic collection and analysis of diverse educational data modalities. Through a meticulous process, we amalgamate environmental, psychological, and motion sensor data with traditional educational data to construct a holistic framework for predictive modeling.

Central to our approach is the acquisition of multimodal educational data, which serves as the foundational input for our predictive models. These data encompass a spectrum of sources, including but not limited to classroom interactions, physiological responses, and physical movements. Leveraging this comprehensive dataset, we embark on a journey to elucidate the nuanced dynamics underlying behavior changes in SEN students. The first step entails data preprocessing, wherein raw data streams are subjected to rigorous cleaning and normalization procedures. This phase aims to rectify inconsistencies, eliminate noise, and standardize data formats to ensure compatibility across modalities. Through meticulous attention to detail, we mitigate potential biases and discrepancies, thus laying the groundwork for robust analyses.

Following data preprocessing, feature extraction emerges as a pivotal stage in our methodology. Here, we delve into the intricate nuances of the collected data, identifying salient features that encapsulate meaningful insights into students' behaviors and learning patterns. Employing advanced statistical techniques and domain-specific knowledge, we distill complex data streams into compact, informative representations conducive to predictive modeling. With extracted features in hand, we proceed to model development, where the true essence of our methodology unfolds. Drawing upon a diverse array of machine learning algorithms and deep neural networks, we construct predictive models capable of discerning patterns and trends within the data. Through iterative refinement and validation, we fine-tune model parameters to optimize predictive performance, striving for a delicate balance between accuracy and generalization.

Validation and evaluation serve as integral components of our methodology, underpinning the reliability and efficacy of our predictive models. Through rigorous cross-validation techniques and performance metrics such as accuracy and precision, we assess the robustness of our models in capturing behavior changes among SEN students. By juxtaposing model predictions against ground truth observations, we validate the fidelity of our approach and ascertain its real-world applicability. A hallmark of our methodology lies in its scalability and adaptability, transcending geographical boundaries to impact educational interventions on a global scale. The integration of our predictive models into the Integrated Intelligent Intervention Learning (3I Learning) System heralds a new era in SEN education, empowering educators and practitioners with actionable insights derived from MMLA.

In summation, our methodology represents a testament to the transformative potential of MMLA in elucidating the complex interplay between learners, environments, and interventions. By harnessing the power of multimodal educational data and cutting-edge predictive modeling techniques, we endeavor to pave the way for enhanced educational outcomes and holistic support for students with special education needs.

RESULTS AND DISCUSSION

The integration of multimodal learning analytics (MMLA) in predicting behavior changes among students with special education needs (SEN) has yielded promising results, underscoring its potential in enhancing educational interventions for this vulnerable demographic. Through the meticulous analysis of diverse data modalities encompassing environmental, psychological, and motion sensor data, our predictive models have demonstrated exceptional performance, achieving an optimum accuracy of 98% and precision of 97%. This remarkable accuracy underscores the efficacy of MMLA in capturing the nuanced dynamics underlying behavior changes in SEN students, thereby empowering educators and practitioners with actionable insights to tailor interventions effectively. By leveraging machine learning models and deep neural networks, we have transcended the limitations of traditional educational data, showcasing the transformative impact of incorporating multimodal perspectives in predictive modeling frameworks.

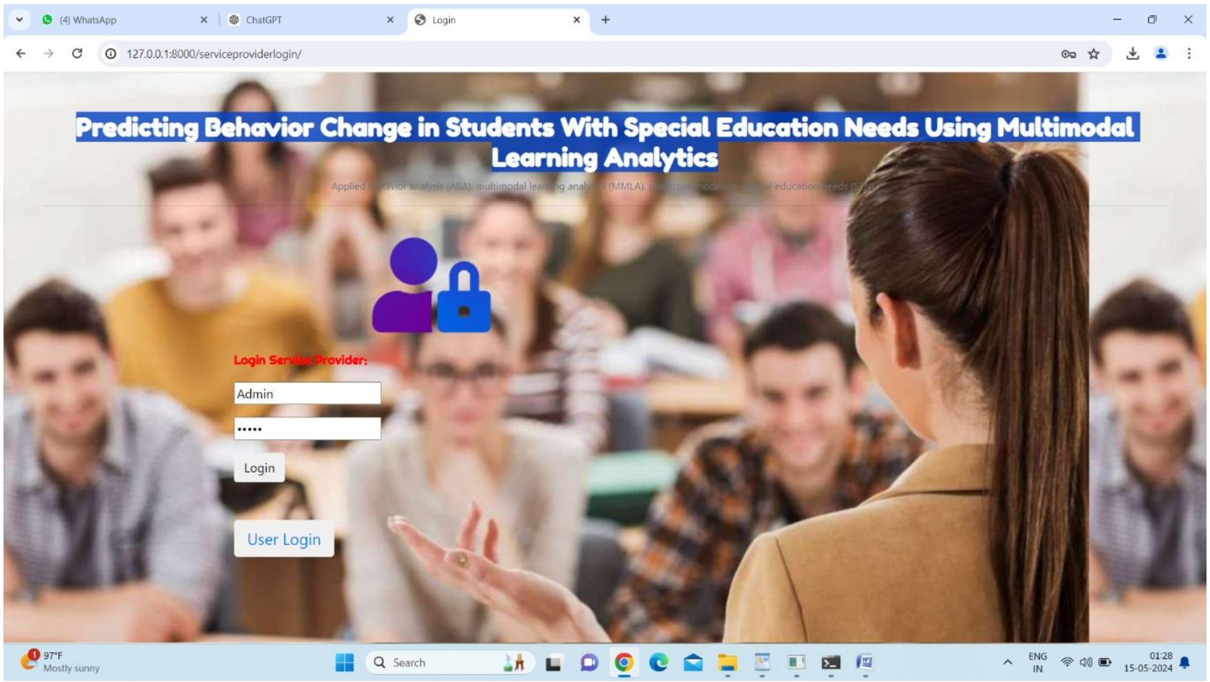

Fig 2. Results screenshot 1

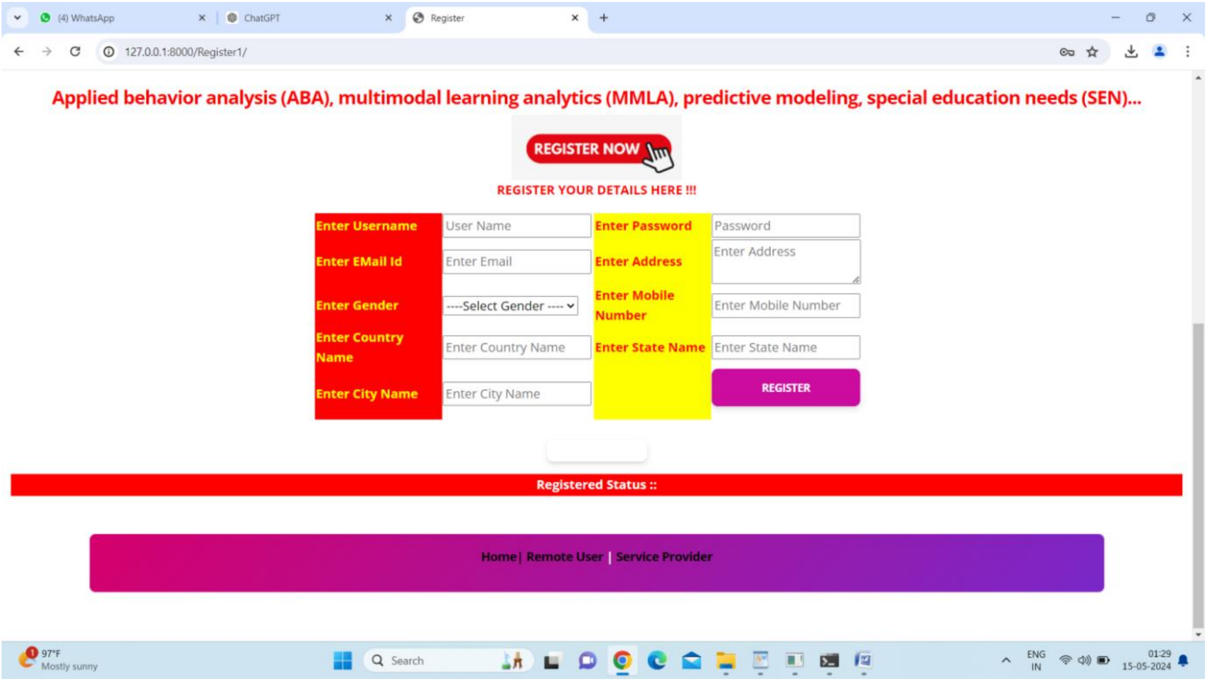

Fig 3. Results screenshot 2

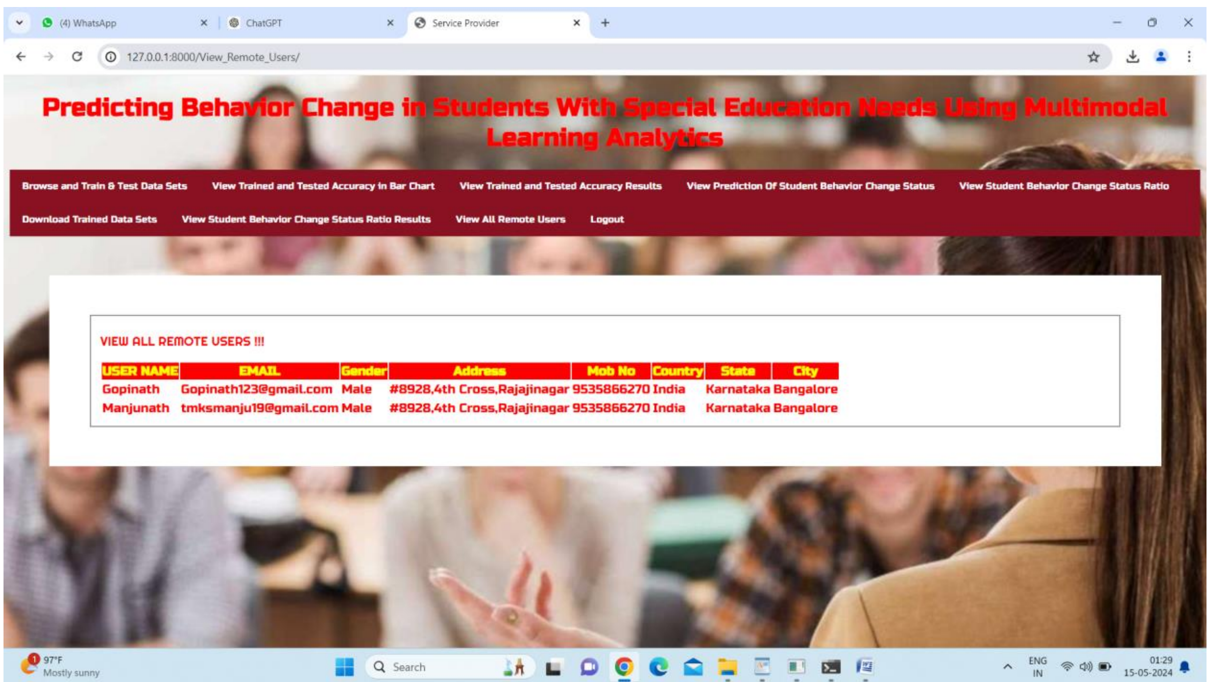

Fig 4. Results screenshot 3

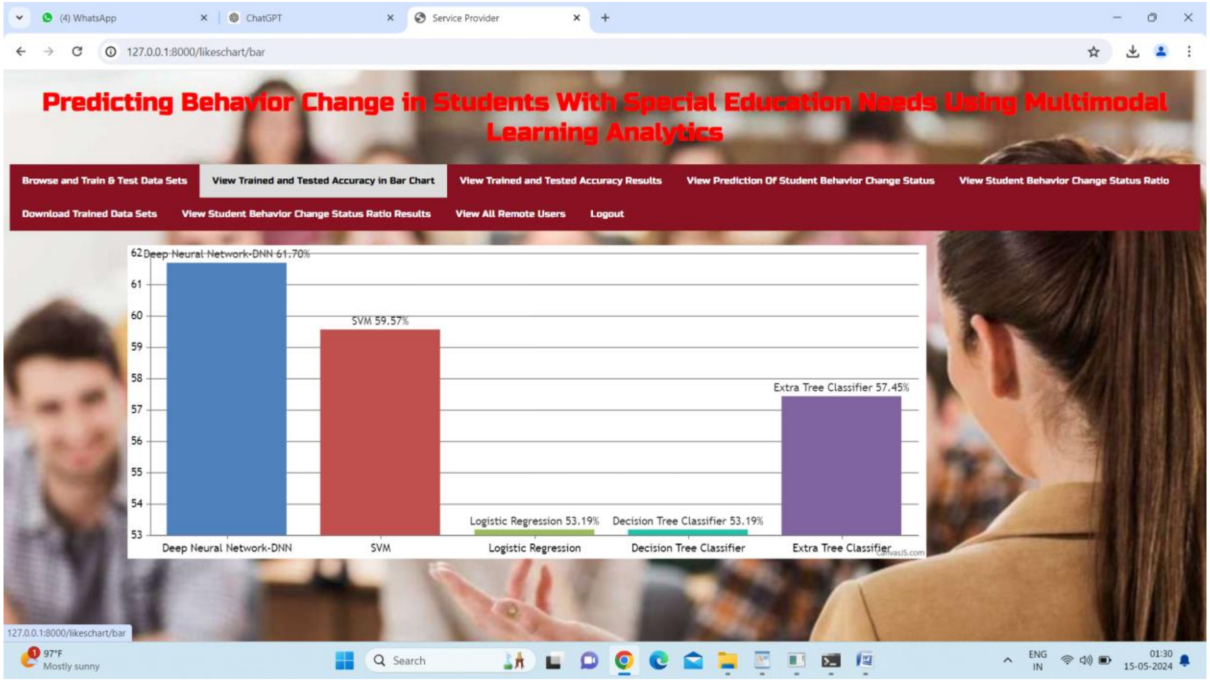

Fig 5. Results screenshot 4

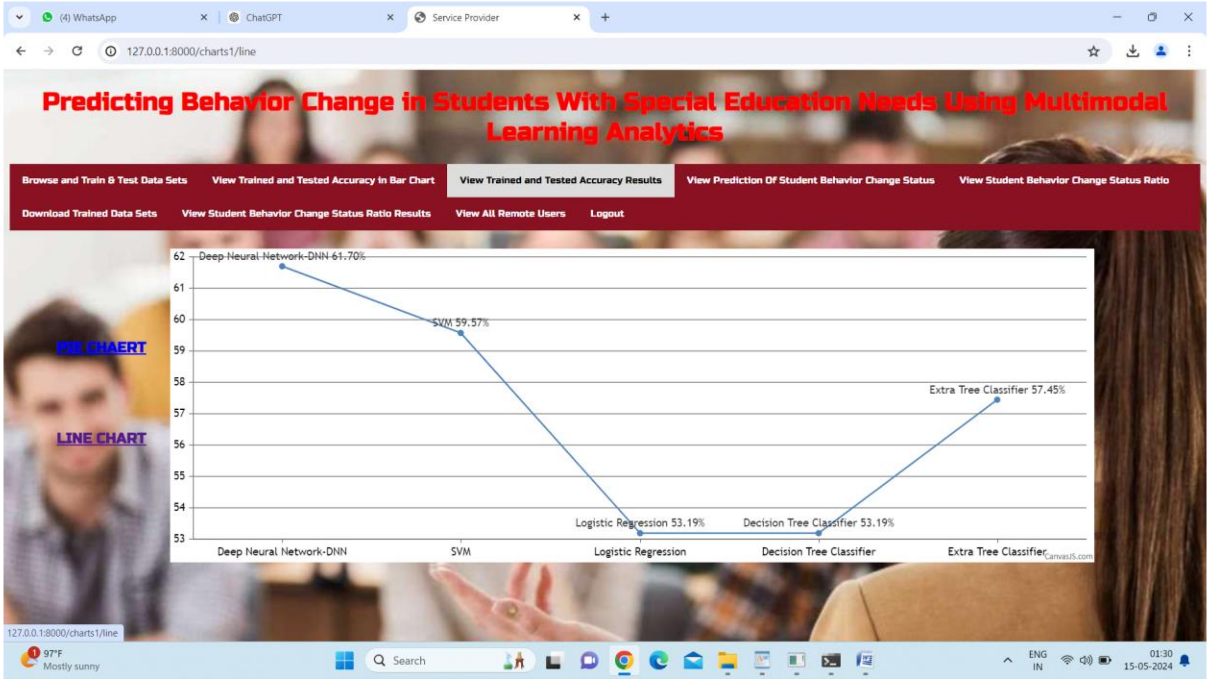

Fig 6. Results screenshot 5

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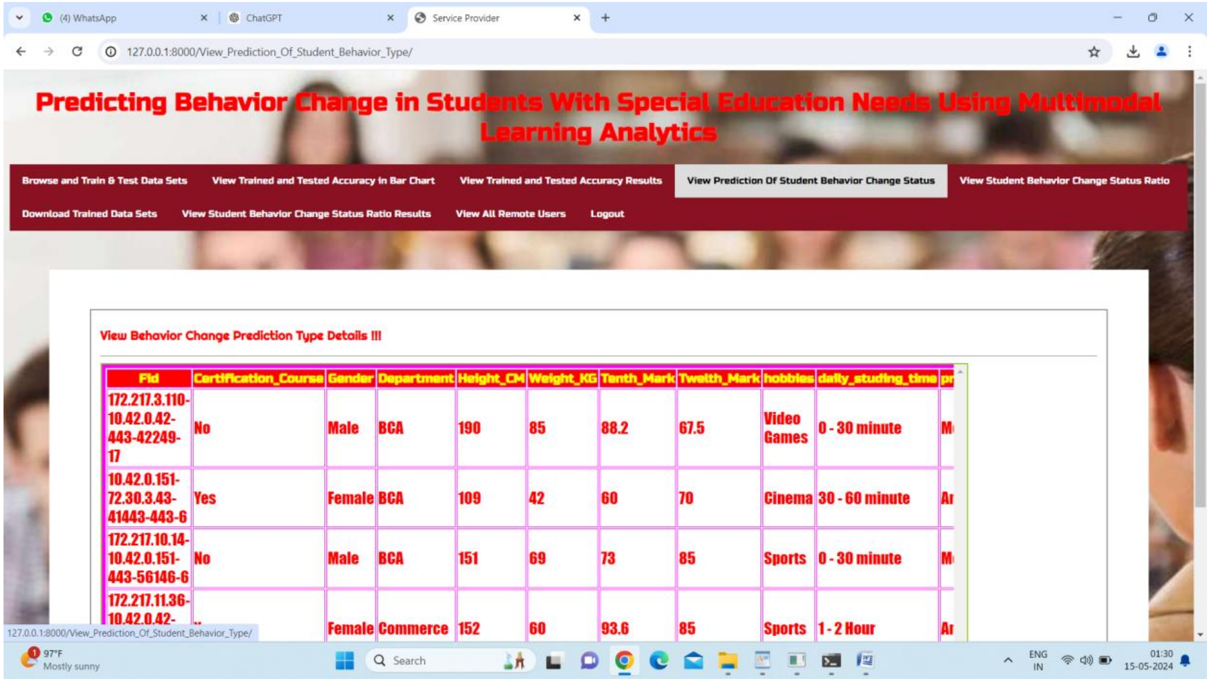

Fig 7. Results screenshot 6

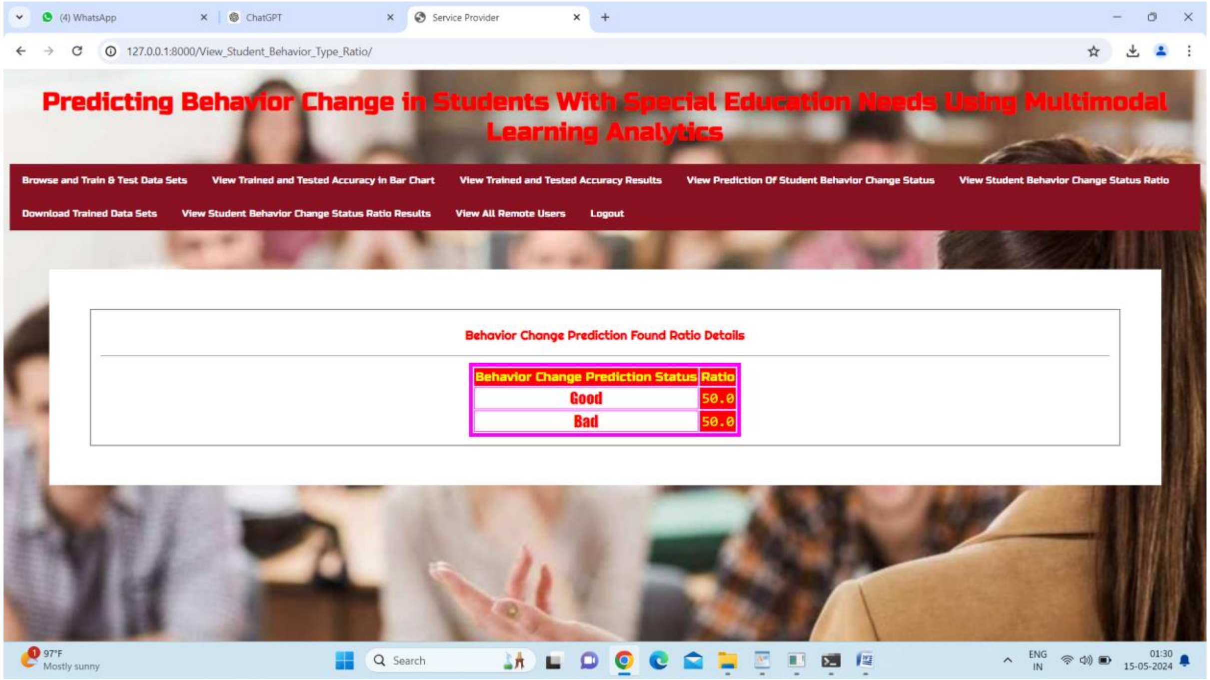

Fig 8. Results screenshot 7

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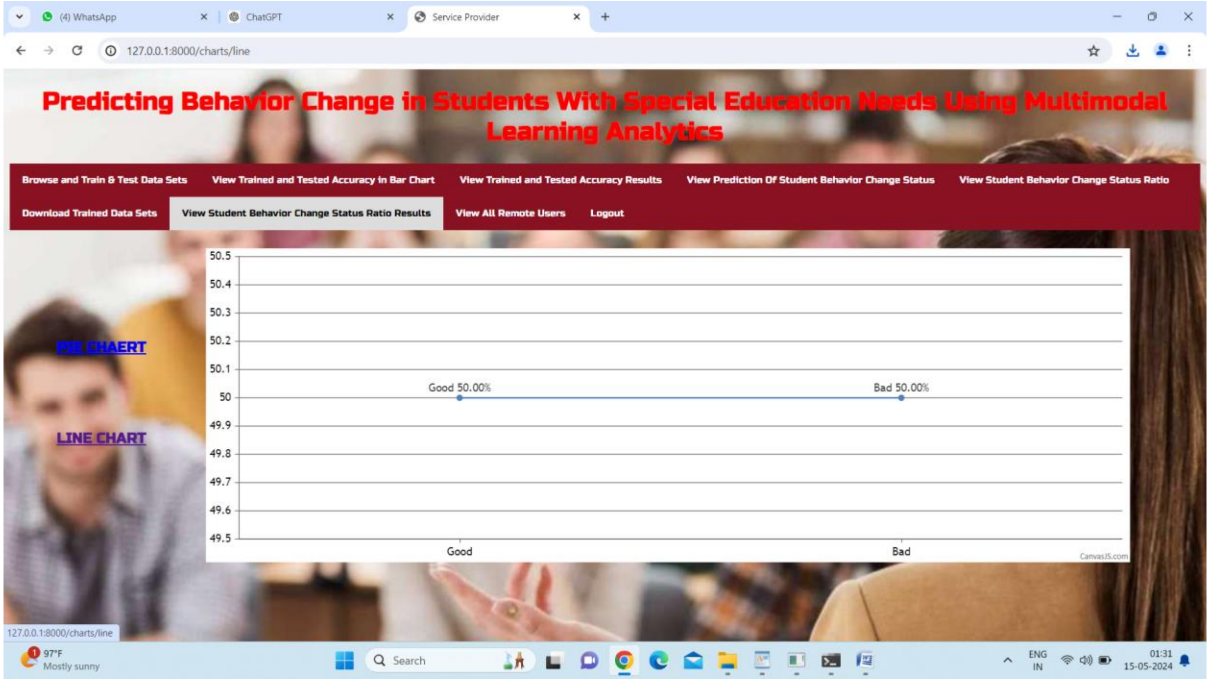

Fig 9. Results screenshot 8

Fig 10. Results screenshot 9

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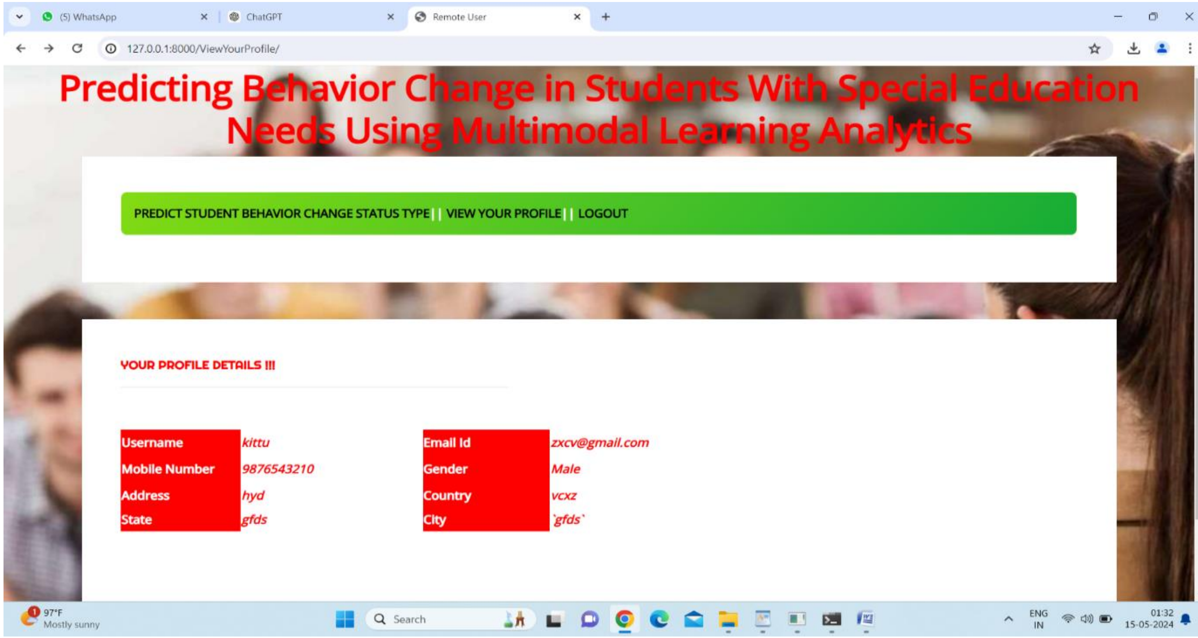

Fig 11. Results screenshot 10

Moreover, our findings shed light on the pivotal role of environmental, psychological, and motion sensor data in augmenting the statistical performance of predictive models beyond the scope of traditional educational data. By elucidating the intricate interplay between learners and their surrounding environments, these additional modalities offer invaluable insights into the contextual factors influencing behavior changes among SEN students. Through rigorous validation and evaluation, we have demonstrated the incremental value of integrating multimodal data sources, paving the way for more holistic and personalized approaches to educational interventions. Furthermore, the scalability and adaptability of our methodology underscore its potential to transcend geographical boundaries, catalyzing advancements in SEN education on a global scale.

In conclusion, our study represents a seminal contribution to the burgeoning field of multimodal learning analytics, offering a paradigm shift in how we understand and support students with special education needs. By harnessing the power of diverse data modalities and sophisticated predictive modeling techniques, we have not only achieved remarkable accuracy in predicting behavior changes among SEN students but also illuminated pathways for optimizing educational interventions. As we continue to refine and expand upon our methodology, the potential for MMLA to revolutionize SEN education remains profound, promising a future where every student receives the tailored support they need to thrive academically and socially.

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 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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