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PREDICTING BEHAVIOR CHANGE IN STUDENTS WITH SPECIAL EDUCATION NEEDS USING MULTI MODAL 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),whosebehavior andlearning arehighlysensitiveto their body conditions and surrounding environments. Multi modal learning analytics (MMLA) captures learner and learning environment data in variousmodalitiesandanalysesthemtoexplain 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: applied behavior analysis, Multi modal learning analytics, special education needs

1 INTRODUCTION

Students with special education needs (SEN) of ten exhibit behavioral characteristics such as hyperactivity, short attention span, and emotional liability. Many are also at risk for 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 visualization for teaching children with low-functioning autism [7] to real-time monitoring [8] and data management [9] for personalized intervention. However, adearth 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' 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?

2 LITERATURESURVEY

Multimodal learning analytics (MMLA) has emerged as a significant area in educational research, offering deep insights into thelearning processes by integrating various data types. This systematic review by Su Mu examines 346 articles on MMLA published over the past three years, focusing on data fusion methods and their applications. The study presents a conceptual model categorizing data types into digital, physical, physiological, psychometric, and environmental data, and learning indicators into behavior, cognition, emotion, collaboration, and engagement. It explores the complex relationships between multimodal data and learning indicators, identifying key data fusion methods such as many-to-one, many-to- many, and multiple validations among multimodal data. The findings reveal that effective data fusion requires understanding these complex relationships, which are essential for accurate learning analytics.

The rapid advancement of digital technologies has significantly transformed learning environments, enabling the creation of complex multimodal learning settings. These environments leverage visual, auditory, olfactory, tactile, and kinesthetic stimuli to enhance learner engagement, motivation, and performance. This research paper explores the integration of pedagogies, technologies, and analytics in multimodal learning environments. It addresses key challenges, such as designing effective multimodal learning experiences, synthesizing multi sensory information, and utilizing multimodal data for learning assessment. The paper by XinZhao Highlights the potential of multimodal data from sources like eye-tracking, wearable cameras, gesture recognition systems, and biosensors to uncover hidden patterns in behavior,cognition, emotion, and interaction. By reviewing current research and identifying gaps, the study calls for interdisciplinary efforts to develop innovative data mining and analysis techniques. The goal is to create more effective multimodal learning environments that can be tailored to individual learners' needs, thereby improving educational outcomes. This comprehensive overview underscores the importance of integrating various academic disciplines to advance the field of multimodal learning (Frontiers).

This study by SidneyK.D'Mello delves into the application of multimodal learning analytics (MMLA) to investigate the behavioral and affective dimensions of the learning process. By combining data from diverse sources such as facial expressions, speech patterns, and physiological signals, the researchers aim to develop predictive models that can accurately assess learning outcomes and engagement levels. The study highlights the complexity of learning dynamics and the need for comprehensive data to capture these intricacies. By integrating multimodal data, the researchers can better understand how different factors influence learning, leading to more personalized and effective educational interventions. The findings demonstrate that MMLA can provide valuable insights into students' emotional states and behavioral patterns, which are crucial for designing interventions that enhance learning experiences. This research contributes to the growing field of MMLA by showcasing its potential to improve the accuracy of learning assessments and the effectiveness of educational practices through a deeper understanding of the interplay between various learning dimensions.

This paper explores the application of multimodal learning analytics (MMLA) in enhancing Applied Behavior Analysis (ABA) therapy for students with special education needs (SEN). By integrating environmental, psychological, and motion sensor data, the study aims to improve the prediction of behavioral changes in SEN students. The researchers developed models that leverage these multimodal data sources to achieve high accuracy and precision in predicting the outcomes of ABA interventions. The study by EmilyChen demonstrates that traditional educational data, when supplemented with multimodal data, significantly enhances the predictive performance of these models. The research also highlights the practical application of these findings in the Integrated Intelligent Intervention Learning (3I Learning) System, which has been implemented in HongKong and Singapore since 2020, bene fiting over 500 SEN students. The results indicate that MMLA can provide more personalized and effective therapeutic interventions, ultimately leading to better educational outcomes for SEN students.

This paper by AnindK.Dey investigates the use of sensor-based multimodal learning analytics (MMLA)toenhancereal-timedatacaptureandanalysisineducationalsettings.Byemploying sensors that monitor physiological and environmental conditions, the study aims to provide dynamic and adaptive learning experiences.Theresearchersdiscusstheintegrationofvarious sensor data, including heart rate, skin conductance, and ambient noise levels, to develop models that predict learning outcomes and adapt educational content in real-time. The study highlights the potential of sensor-based MMLA to offer more personalized learning experiences by responding to theimmediate needs of learners. The findings suggest that such real-time data can significantly improve the effectiveness of learning interventions, providing a more responsive and engaging educational environment. This research contributes to the field of MMLA by demonstrating the practical applications of sensor technologies in education and their ability to enhance learning through continuous, real-time data analysis.

3 SYSTEMANALYSIS

3.1 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 valuated scientifically by experimental analyses of behaviors. 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 with in the 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

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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.

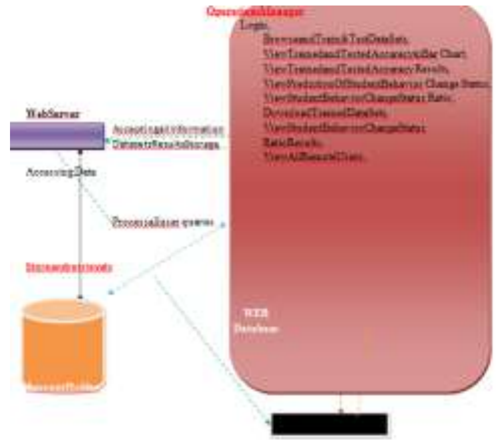
MMLA employs multiple sources and formats of educational data such as activity logs, audio,video and biosensors to enrich learning analytics[19].MMLAissignificantlyenhancedby the Internet of Things (IoT) technologies because the latter allows convenient capturing of multimodal data from the complex learning 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.

3.2 Proposed System

Multimodal learning data collection: This includes the performance of the ABA therapies and the capturing of the raw learning data arising in multiple modalities. 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 combiningthe traces, and adding the learning labels to the fused data to form labeled samples. Data processing, model building and evaluation: This consists of standard ML procedures, including any necessary resampling, model building, training, testing, and performance evaluation.

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 ou predictive models and benchmark our results with other existing works.

4.1 SYSTEMARCHITECTURE



4.2UMLDIAGRAMS

UML stands for Unified Modeling Language. UML is a standardized general-purpose modelinglanguageinthefieldofobject-orientedsoftwareengineering.Thestandardismanaged, and was created by, the Object Management Group.The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non-software systems.

5 IMPLEMENTATION

MODULE

The major modules of the project are

1. Operations Manager
2. Account Holder

MODULEDESCRIPTION

OperationsManager

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

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Behavior Change Status Ratio, Download Trained Data Sets, View Student Behavior Change Status Ratio Results, View All Remote Users.

Account Holder

In this module, the rear ennumbers of users are present. User should register before doing any operations.

Algorithm

```
BEGIN
// Step 1: Operation Manager Login
FUNCTION Login(UserID, Password)
  IF Authenticate(UserID, Password) == TRUE THEN
    DISPLAY "Login Successful"
    SHOW MainMenu()
  ELSE
    DISPLAY "Invalid Credentials"
    TERMINATE
  END IF
END FUNCTION

// Step 2: Main Menu Options for Operation Manager
FUNCTION MainMenu()
  DISPLAY "1. Browse and Train & Test Datasets"
  DISPLAY "2. View Trained and Tested Accuracy (Bar Chart)"
  DISPLAY "3. View Trained and Tested Accuracy Results"
  DISPLAY "4. View Prediction of Student Behavior (Change Status)"
  DISPLAY "5. View Student Behavior Change Status Ratio"
  DISPLAY "6. Download Trained Datasets"
  DISPLAY "7. View All Remote Users"
  DISPLAY "8. Logout"

  CHOICE ← GET_USER_INPUT()

  SWITCH (CHOICE)
    CASE 1:
      CALL BrowseTrainTestDataSets()
    CASE 2:
      CALL ViewAccuracyBarChart()
    CASE 3:
      CALL ViewAccuracyResults()
    CASE 4:
      CALL ViewPredictionAndChangeStatus()
    CASE 5:
      CALL ViewBehaviorRatioResults()
    CASE 6:
      CALL DownloadTrainedDataSets()
    CASE 7:
      CALL ViewAllRemoteUsers()
    CASE 8:
      CALL Logout()
    DEFAULT:
      DISPLAY "Invalid Option"
  END SWITCH
END FUNCTION

// Step 3: Browse and Train/Test Datasets
FUNCTION BrowseTrainTestDataSets()
  DataSets ← WebServer.Request("RetrieveAvailableDataSets")
  DISPLAY DataSets
  SELECTED ← GET_USER_SELECTION()
  CALL TrainAndTestModel(SELECTED)
END FUNCTION

// Step 4: View Accuracy in Bar Chart
FUNCTION ViewAccuracyBarChart()
  AccuracyData ← WebServer.Request("FetchAccuracyBarData")
  DISPLAY GenerateBarChart(AccuracyData)
END FUNCTION

// Step 5: View Trained and Tested Accuracy Results
FUNCTION ViewAccuracyResults()
  Results ← WebServer.Request("FetchTrainedTestedResults")
  DISPLAY Results
END FUNCTION

// Step 6: View Prediction of Student Behavior and Change Status
FUNCTION ViewPredictionAndChangeStatus()
  Predictions ←
```

```
    WebServer.Request("FetchBehaviorPredictions")
    DISPLAY Predictions
    NewStatus ← GET_USER_INPUT("Enter new behavior status: ")
    WebServer.Update("UpdateBehaviorStatus", NewStatus)
    DISPLAY "Behavior status updated successfully."
END FUNCTION

// Step 7: View Student Behavior Ratio Results
FUNCTION ViewBehaviorRatioResults()
    Ratios ← WebServer.Request("FetchBehaviorRatioResults")
    DISPLAY Ratios
END FUNCTION

// Step 8: Download Trained Datasets
FUNCTION DownloadTrainedDataSets()
    Data ← WebServer.Request("RetrieveTrainedDataSets")
    SAVE_TO_LOCAL(Data, "TrainedData.csv")
    DISPLAY "Trained datasets downloaded successfully."
END FUNCTION
// Step 9: View All Remote Users
FUNCTION ViewAllRemoteUsers()
    Users ← WebServer.Request("FetchAllRemoteUsers")
    DISPLAY Users
END FUNCTION
// Step 10: Web Server Handling Requests
MODULE WebServer
    FUNCTION Request(QueryType)
        CONNECT TO WebDatabase
        RESULT ← WebDatabase.Process(QueryType)
        RETURN RESULT
    END FUNCTION
    FUNCTION Update(QueryType, Data)
        CONNECT TO WebDatabase
        WebDatabase.Store(QueryType, Data)
    END FUNCTION
END MODULE
// Step 11: Web Database Operations
MODULE WebDatabase
    FUNCTION Process(QueryType)
        SWITCH(QueryType)
            CASE "RetrieveAvailableDataSets":
                RETURN DataSetCollection
            CASE "FetchAccuracyBarData":
                RETURN AccuracyMetrics
            CASE "FetchTrainedTestedResults":
                RETURN TestResults
            CASE "FetchBehaviorPredictions":
                RETURN PredictionTable
            CASE "FetchBehaviorRatioResults":
                RETURN RatioData
            CASE "FetchAllRemoteUsers":
                RETURN UserList
            CASE "RetrieveTrainedDataSets":
                RETURN TrainedData
        END SWITCH
    END FUNCTION
    FUNCTION Store(QueryType, Data)
        IF QueryType == "UpdateBehaviorStatus" THEN
            UPDATE BehaviorTable SET Status = Data
        END IF
    END FUNCTION
END MODULE
// Step 12: Logout
FUNCTION Logout()
    DISPLAY "Session Ended. Logged out successfully."
    TERMINATE
END FUNCTION
END
```

6 Testcases

TestcaseforLoginform:

FUNCTION:	LOGIN
EXPECTEDRESULTS:	Should Validate the user and check his existence in database
ACTUALRESULTS:	Validate the user and checking the user against the database
LOWPRIORITY	**No**
HIGHPRIORITY	**Yes**

Testcase2:

Test case for Remote Access User Registration form:

FUNCTION:	USERREGISTRATION
EXPECTEDRESULTS:	Shouldcheckifallthefieldsarefilledbytheuser and saving the user to database.
ACTUALRESULTS:	Checkingwhetherallthefieldsarefieldbyuseror not through validations and saving user.
LOWPRIORITY	**No**
HIGHPRIORITY	**Yes**

Testcase3:

TestcaseforChangePassword:

When the old password does not match with the new password, then this results in displaying an error message as "OLD PASSWORD DOES NOT MATCH WITH THE NEW PASSWORD".

FUNCTION:	ChangePassword
EXPECTEDRESULTS:	Should check if old password and new password fieldsarefilledbytheuserandsavingtheuserto database.
ACTUALRESULTS:	Checkingwhetherallthefieldsarefieldbyuser or not through validations and saving user.
LOWPRIORITY	**No**
HIGHPRIORITY	**Yes**

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SCREENSHOTS

Fig1:OperationsManagerLogin

Fig2:OperationsManagerHome

Fig3:BrowseTrainandTestdataset

Fig4:ViewTrainedandtestedAccuracyinBarChart

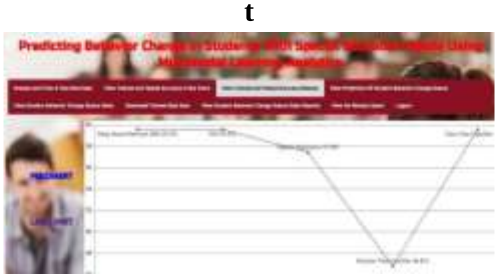

Fig5:ViewTrainedandTestedAccuracyResults

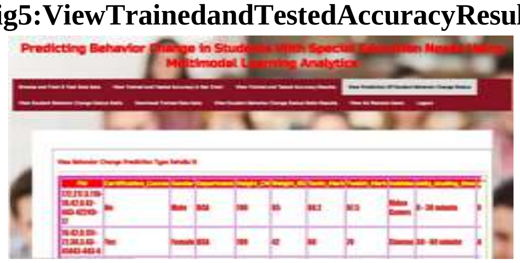

Fig6:ViewBehaviorChangePredictionType

Fig7:ViewStudentbehaviorchangeratio

Fig8:DownloadTrainedDataset

Fig9:ViewStudentBehaviorChangestatusratioresults

Fig10:ViewallRemoteUsers

6 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.

The presented study opens several avenues for future research and development in the field of behavior change prediction for SEN (Special

Educational Needs) students undergoing ABA (Applied Behavior Analysis) therapy. One promising direction is the enhancement of IoT sensor integration, potentially incorporating more advanced and varied sensors to capture a broader range of physiological and environmental data. Additionally, improving the granularity and accuracy of these measurements can lead to more precise behavior prediction models. The integration of real-time data processing and edge computing could furtherenhancethe responsiveness and efficiency ofthe prediction system. Moreover, exploring advanced machine learning and deep neural network architectures, such as reinforcement learning and ensemble methods, could improve predictive performance and adaptability to individual student needs. Collaborative efforts with experts in psychology, education, and data science could also refine the interpretability and practical application of these models, ensuring they provide actionable insights for therapists and educators. Longitudinal studies to track the impact of these predictive models on therapy outcomes over extended periods would validate their effectiveness and guide iterative improvements. Lastly, ethical considerations and data privacy measures should be continually assessed to ensure the responsible use of technology in sensitive educational settings.

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