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Predictive Modeling For Children ADHD Detection Through Behavioural Analytics

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Abstract— This study presents a novel approach to predictive modelling in the context of behavioural analysis in children by integrating Deep Neural Networks (DNNs) with Transformer-based models. The motivation behind this arises from the fact that behavioral data is complicated and frequently contains non-linear connections and temporal dependencies that traditional models struggle to capture effectively. By combining strengths of DNNs in handling non-linear patterns with the Transformer's capability to perform sequential By using self-attention processes to process data, the suggested hybrid model seeks to enhance the accuracy and interpretability of predictions. The methodology involved extensive data preprocessing, including normalization, augmentation, and feature engineering to improve the input data's quality. Two distinct architectures were created, with the DNN capturing intricate feature interactions and the Transformer focusing on temporal aspects of the behavioral data. The outputs of both models were fused through a weighted aggregation layer, optimizing predictive performance. Regularization strategies like L2 regularization, batch normalization, and dropout were employed avoid being too oversized and ensure model broad generalization. Hyperparameter tuning was conducted using utilizing Bayesian optimization and grid search leading to the selection of the optimal model configuration. The model's interpretability was enhanced employing LIME (Local Interpretable Model agnostic Explanations) and SHAP (Shapley Additive explanations), which provided insights into the key behavioral features driving predictions. The results demonstrated that the hybrid model outperformed traditional approaches, with significant improvements in accuracy, precision, and recall. The model's robustness was confirmed through rigorous assessment with the use of ROC-AUC and F1-Score measures, along with deployment in real-world scenarios where it showed stable performance over time. This study highlights the potential of hybrid models in advancing the field of predictive modeling for behavioral analysis, offering a powerful and interpretable tool for researchers and practitioners working with children's behavioral data.

Keywords: ADHD, behavioural activity, children, machine learning, prediction

I. INTRODUCTION

Behavioral analysis in children plays a critical role in early identification of developmental disorders, academic challenges, and social adaptability issues. Predictive modeling based on behavioral data can offer significant insights into these areas, enabling timely interventions. However, traditional models often struggle with the complexity and variability inherent in children's behavior. Recent advances in deep learning, particularly Deep Neural Networks (DNNs) and Transformer-based models offer fresh chances to improve the predictability of capturing intricate patterns in behavioral data.

This study focuses on developing advanced predictive models using DNNs and Transformers to analyze and forecast behavioral outcomes in children. By leveraging key factors such as crossentropy loss, the softmax function, attention mechanisms, and mean squared error, the proposed models aim to surpass the limitations of existing approaches. Cross-entropy loss and the softmax function are employed to optimize classification tasks within the behavioral data, allowing the models to effectively distinguish between various behavioral states. One of Transformer's main components is the attention mechanism models, enhances the ability to One of Transformer's main components is the attention mechanism for understanding complex behavioral sequences. Furthermore, mean squared error is used to refine regression tasks, ensuring precise prediction of continuous behavioral metrics.

The integration of these advanced techniques addresses several challenges inherent in behavioral analysis. First, the high dimensionality of behavioral data, which often includes a wide range of factors such as social interactions, cognitive performance, and emotional responses, can be effectively handled by the DNNs' ability to learn hierarchical representations. Second, the temporal nature of behavioral development is captured through the Transformer's sequential processing capabilities, allowing the model to consider both short-term fluctuations and long-term trends in a child's behavior.

Moreover, the proposed models incorporate multi-modal data inputs, combining traditional behavioral assessments with more recent innovations such as wearable device data and digital interaction logs. This comprehensive approach provides a more perspective on a child's conduct in various situations and time scales. The models are designed to be interpretable, with attention visualizations and feature importance investigations that provide light on the variables influencing behavioral predictions.

The study's approach involves a multi-stage process. Initially, extensive data preprocessing is performed to handle missing values, normalize diverse data sources, and create meaningful feature representations. The model architecture is then carefully designed, with hyperparameter tuning conducted through crossvalidation maximize output. Additionally, methods for transfer learning that make use of pretrained models are examined on larger datasets to improve generalization on smaller, domainspecific behavioral datasets.

Evaluation of the models is conducted using a diverse set of metrics, including accuracy, For classification tasks, the F1 score and area under the ROC curve are used; for regression tasks, the mean absolute error and Rsquared values are used and mean absolute error and R-squared values for regression tasks. Comparisons are made in opposition to established machine learning techniques like support vector machines and random forests, as well as simpler neural network architectures, to quantify the improvements offered by the advanced models.
The potential applications of these models span various domains within child development. In educational settings, they can assist in early identification of learning difficulties and personalization of teaching strategies. In clinical contexts, the models can support diagnosis and treatment planning for developmental disorders. Additionally, the predictive capabilities of these models can inform policy decisions related to early childhood interventions and resource allocation.
By integrating these factors, the proposed models aim to provide more accurate and reliable predictions of children's behavioral outcomes. This paper discusses the methodology used to build these models, evaluates their performance against existing methods, and explores their potential applications in educational and clinical settings. The research's conclusions add to the expanding field of predictive modeling in behavioral analysis, offering novel insights and practical solutions for improving child development monitoring.

II. RELATED WORK

The application of multimodal learning analytics (MMLA) has been utilized to forecast the behaviors of students with special education needs (SEN) who engage in applied behavior analysis (ABA) therapies [3]. Researchers have employed multimodal educational data to develop machine learning models and deep neural networks capable of predicting behavioral changes in SEN students with an accuracy of 98% and a precision of 97%. Furthermore, it was demonstrated that incorporating environmental, psychological, and motion sensor data can significantly enhance the statistical performance of predictive models when combined with traditional educational data [1]. This research has been implemented in the Integrated Intelligent Intervention Learning (3I Learning) System, which has improved intensive ABA therapies for over 500 SEN students in Hong Kong and Singapore since 2020. Students with special education needs (SEN) frequently display behavioral traits such as hyperactivity, limited attention spans, and emotional instability, which can result in academic and social challenges.
Inappropriate behaviors, particularly those associated with autism spectrum disorders (ASD), are often linked to abnormalities in brain development, while certain learning disabilities may have genetic foundations. Contextually inappropriate actions, including aggression and self-harm, can impede the social and personal growth of SEN students [2]. Encouraging positive behaviors is essential for achieving favorable learning outcomes in special education. Applied behavior analysis (ABA) therapy serves as an intervention strategy aimed at modifying the behaviors of SEN students, grounded in principles such as reinforcement and stimulus control. A systematic review of ABA technologies, which encompasses web-based services, data visualization, real-time monitoring, and data management, has indicated their potential in promoting socially significant outcomes [8]. Nevertheless, there remains a gap in research focused on predicting outcomes related to ABA. Learning analytics (LA) represents a data-driven approach that is well-suited for enhancing ABA-related technologies, as it is frequently utilized in educational settings to analyze and optimize learning processes and environments, thereby potentially improving existing methodologies.

One of the most common neurodevelopmental and psychiatric conditions is attention deficit hyperactivity disorder (ADHD).on a global scale. Approaches utilizing EEG signals are essential for the early identification and classification of ADHD. Nevertheless, the use of full EEG channels for diagnosing children with ADHD can result in computational challenges and issues related to overfitting.To mitigate these concerns, a machine learning (ML) framework for ADHD detection was developed, focusing on the identification of optimal channels and their key features. This research employed support vector machine and t-test methodologies to individually select optimal channels, alongside a hybrid approach that integrates both methods [10]. The LASSO logistic regression model was utilized to identify significant features from the chosen channels. A total of six ML classifiers were implemented for ADHD detection, with their effectiveness assessed through accuracy measurements and AUC (area under the curve). The study included 101 children aged between 7 and 12 years, of which 61 were diagnosed with ADHD. The GPbased classifier showed a 97.53% accuracy rate and a 0.999 AUC, reflecting a 3% enhancement compared to earlier methodologies.
The existing methodology for ADHD detection through behavioural analysis typically involves a multi-faceted approach that combines clinical assessment, standardized rating scales, and observational data [7]. This comprehensive process aims to capture a holistic perspective on how a person behaves in different situations and environments.

Clinical assessment forms the foundation of the diagnostic process. Experienced mental health professionals, such as psychiatrists or clinical psychologists, conduct in-depth interviews with the individual suspected of having ADHD [5], as well as with parents, teachers, and other relevant caregivers. These interviews explore the the person's past developmental trajectory, their current symptoms, and how these symptoms affect their day-to-day functioning. The clinician carefully

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evaluates the presence, severity, and duration of ADHD symptoms, considering both inattention and hyperactivityimpulsivity dimensions [13].
Standardized rating scales play a crucial role in quantifying and comparing behavioural symptoms. widely used scales include the Vanderbilt ADHD Diagnostic Rating Scale, the Conners' Rating Scales, and the ADHD Rating Scale-IV [4]. These instruments provide a structured method for parents, teachers, and sometimes the individuals themselves to report on specific behaviours associated with ADHD. The use of multiple informants helps to establish the pervasiveness of symptoms across different environments, which is a key diagnostic criterion for ADHD [16].

Predictive modeling in behavioral analysis has traditionally relied on statistical methods and classical machine learning algorithms like Support vector machines (SVMs), decision trees, and logistic regression. These techniques have been used to identify patterns in children's behavior and predict outcomes such as academic performance or the likelihood of developing behavioral disorders [14]. While these models have provided valuable insights, they often struggle to capture the complex, non-linear relationships present in behavioral data.
The limitations of classical models stem from their inability to handle high-dimensional data and learn intricate patterns without extensive feature engineering. They often struggle with the variability and noise inherent in behavioral data, leading to issues like overfitting or underfitting. These models typically assume linearity and independence among features, which is rarely the case in real-world behavioral datasets. Consequently, their predictions can lack robustness and fail to generalize across different populations or contexts.
Deep Neural Networks (DNNs) have addressed some of these constraints by explicitly deriving hierarchical representations from the data, reducing the need for manual feature extraction. However, DNNs still face challenges such as vanishing gradients, difficulty in capturing long-range dependencies, and the requirement for large labeled datasets, which are not always available in behavioral studies.

Transformer-based models, introduced more recently, offer significant improvements through the use of self-attention processes to record intricate relationships between data sequences. Despite their advantages, these models are computationally intensive and can suffer from overfitting, particularly when applied to small datasets common in behavioral research. In summary, while existing models have made progress in predictive behavioral analysis, they are often limited by their inability to fully capture the complexity of children's behavior. Emphasizes the requirement for sophisticated models that are more adept at handling the complexities of behavioral data, leading to more accurate and reliable predictions. Hybrid models that integrate the benefits of several strategies As these advancements continue, the potential for more accurate and nuanced predictions in behavioral analysis grows. This could lead to earlier interventions, more personalized support strategies, and improved outcomes for children facing behavioral challenges. However, it's crucial to balance the pursuit of model sophistication with ethical considerations, ensuring that predictive tools are utilized sensibly and with the children's best interests in mind aim to help.
Observational data is another vital component of the existing methodology. This may involve direct observation of the individual in various settings, such as the classroom, home, or clinical environment. Trained professionals may use structured observation protocols to systematically record and analyse specific behaviours indicative of ADHD. Additionally, cognitive and neuropsychological tests may be to evaluate executive performance, impulsivity, and attentiveness. These examinations can give an objective measures of cognitive processes often affected in ADHD.

As part of the diagnosis process, other illnesses that could resemble the symptoms of ADHD are also ruled out. Given that symptoms of ADHD might coincide with those of other diseases including anxiety, depression, or learning impairments, this differential diagnosis is crucial. Medical evaluations may be conducted to exclude physical health issues that could contribute to attention or behavioural problems.
These limitations have motivated researchers to explore more objective and data-driven approaches, such as the predictive modelling techniques discussed earlier but it's crucial to remember that these more recent techniques are intended to complement, rather than replace, the existing clinical methodology. The integration of traditional clinical assessment with advanced analytical tools holds promise for enhancing the accuracy, efficiency, and objectivity of ADHD diagnosis in the future.
The ADHD diagnostic process relies heavily on gathering observational data. This involves professionals watching the individual in different environments, like schools, homes, or medical settings. These experts employ specific observation methods to systematically document and examine behaviors that may indicate ADHD.

III. PROPOSED METHOD

3.1 Data Collection and Preprocessing:

Collect behavioral data from multiple sources such as educational assessments, clinical observations, and parent/teacher questionnaires. Ensure data includes diverse behavioral indicators like emotional responses, cognitive tasks, and social interactions. Handle missing data using imputation techniques or by removing incomplete records if necessary. Remove outliers and reduce noise using filtering techniques. Apply normalization techniques such as min-max scaling or z-score

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normalization to ensure uniformity across features. Generate additional data samples through augmentation techniques, particularly if the dataset is small or imbalanced.

3.2 Model Development
DNN Model Architecture:
Create a multi-layered deep neural network, including: Input Layer: Processed behavioral features. Hidden Layers: For spatial or temporal data, include optional convolutional layers and dense layers with ReLU activation functions.

Output Layer: Softmax or sigmoid activation based on the prediction task (classification or binary).

Transformer Model Architecture:
Develop a Transformer-based model with the following components. Embedding Layer: Convert input sequences into embeddings. Positional Encoding: Add temporal information to the embeddings. Self-Attention Mechanism: Capture dependencies within behavioral sequences. Encoder-Decoder Structure: Implement multi-layered encoders and decoders. Output Layer: Integrate the output from the transformer for prediction.

Hybrid Model Integration:
Combine the outputs from the DNN and Transformer models using a fusion layer. Experiment with different integration strategies, such as weighted aggregation, to optimize the predictive performance.

3.3 Regularization and Optimization:
Apply dropout layers after key hidden layers to prevent overfitting. Use batch normalization to stabilize learning and improve convergence. Introduce L2 regularization to penalize large weights and reduce overfitting. Train the models using adaptive optimization algorithms like Adam or RMSprop for efficient convergence. Perform hyperparameter tuning use Bayesian optimization, grid search, or random search to identify the best model configuration.

$$\mathrm{Softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

Equation 1. Softmax function

$$L_{total} = L_{data} + \lambda L_{regularization}$$

Equation 2. Regularization term

3.4 Model Training and Evaluation:
Make training, validation, and test sets out of the dataset. Educate the DNN, Transformer, and Hybrid models with the validation set applied to the training set for hyperparameter tuning and model selection Use measures like F1-Score, ROCAUC, Accuracy, Precision, and Recall to assess the performance of the model. Generate and analyze confusion matrices to understand the model's predictive accuracy across classes. To determine the relative contributions of the various model components, do ablation investigations. Apply SHAP (SHapley Additive explanations) or LIME (Local Interpretable Modelagnostic Explanations) to analyze the predictions and identify which features are most. Provide visualizations that explain how the model's predictions are made as influenced from "Detection of Counterfeit Medicines Using Hyperspectral Sensing" [19] and it's data model, particularly in the context of complex behavioural data. Deploy the final model in a real-time prediction environment or for batch processing, depending on the application.
Implement APIs or interfaces for easy access and integration with other systems. Establish a tracking system to measure the performance of the model over time detecting any drift in the data or degradation in model accuracy.
To keep the model current and correct, retrain it with fresh data on a regular basis. Ensure that all data collection and analysis processes comply with relevant data privacy laws and ethical guidelines, particularly when dealing with children's data. Examine the model for any possible biases, particularly in the way it forecasts results for various demographic groupings.

IV. ARCHITECTURAL DIAGRAM
The Transformer submodule represents a sophisticated approach to sequential data analysis, incorporating several key components to effectively capture and process complex relationships within the input. At its core, this submodule employs an embedding layer, which transforms raw input data into dense vector representations. These embeddings serve as a foundation for understanding the semantic content of the data.

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Working in tandem with the embedding layer shown in data processing unit of the architecture diagram referenced in Figure 1 has a crucial role in maintaining the sequential nature of the input. In order to ensure that the model can differentiate between various orderings of the identical items, this technique injects information about the relative or absolute location of each element in the sequence.
The Transformer submodule's use of self-attention processes is arguably its most inventive feature. These enable the model to process each element by weighing the relative relevance of various input sequence components, allowing it to capture longrange dependencies and contextual data with remarkable efficiency. The hybrid integration module serves as a bridge

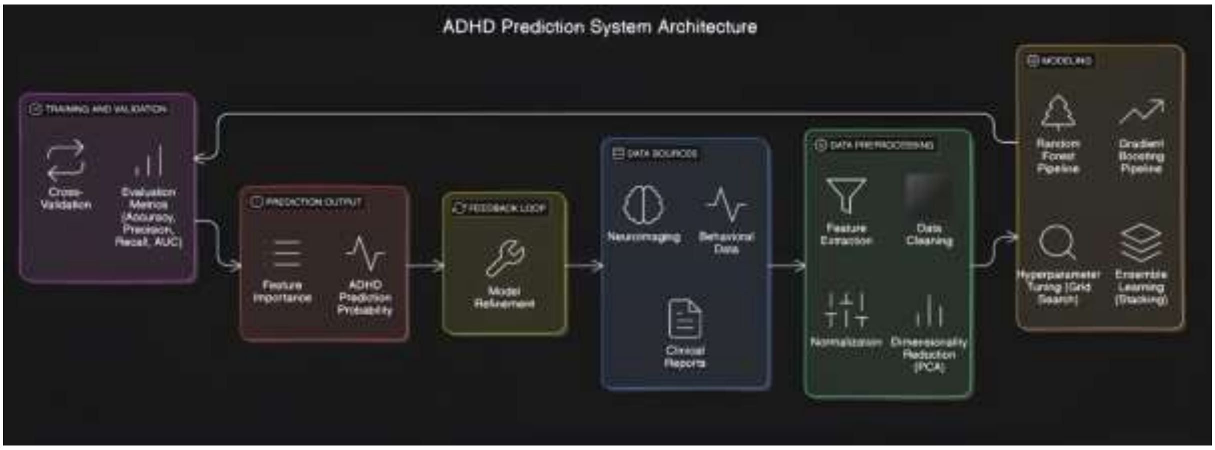

Figure 1. Architecture diagram for predictive modelling for children through behavioural analysis

The proposed diagram outlines a comprehensive architecture for a hybrid deep learning model designed to analyze and predict behavioral patterns. At its core, the system integrates a Using a
Deep Neural Network (DNN) Transformer model, leveraging the strengths of both approaches to process complex behavioral data. The input layer accepts diverse behavioral data types, including emotional responses, cognitive task results, and social interaction metrics. This data then flows through a preprocessing module, where it undergoes normalization, augmentation, missing data handling, and noise reduction to guarantee consistency and quality of data. The feature extraction and engineering module follows, employing techniques such as dimensionality reduction to distill the most relevant behavioral indicators.
This processed data which is shown in Figure 1 then feeds into parallel DNN and Transformer submodules. The DNN submodule consists of multiple hidden layers with ReLU activation dropout layers for enhanced training stability and batch normalization for regularization. The Transformer submodule, on the other hand, utilizes an embedding layer, positional encoding, and self-attention techniques to identify logical connections within the information. A hybrid integration module then combines the outputs from both submodules, potentially using weighted aggregation to optimize decision-making.
between the Transformer submodule and other components of the model. This integration is not a simple concatenation of outputs but rather a nuanced combination that may employ weighted aggregation techniques. By carefully balancing the contributions of different submodules, this approach aims to optimize the overall decision-making process, leveraging the strengths of each component. A variety of regularization and optimization approaches are included to improve the model's performance and avoid overfitting. Dropout, a method that keeps the model from become unduly dependent on training by randomly deactivating some neurons on specific features. L2 regularization adds a penalty term to the loss function, encouraging the model to learn smaller weights and potentially improving generalization.
The choice of optimization algorithm is crucial for efficient training. Advanced methods like Adam or RMSprop are often employed, as comparison to conventional stochastic gradient descent, they may result in faster convergence and greater performance since they adjust learning rates for every parameter.
To further refine the model's performance, a dedicated hyperparameter tuning module is implemented. This module may utilize techniques such such as Bayesian optimization, which makes use of probabilistic models to more effectively traverse the hyperparameter landscape, or grid search, which methodically investigates a predetermined parameter field.

V. RESULT AND DISCUSSION

The implementation of the hybrid model, integrating Deep Neural Networks (DNNs) and Transformer-based architectures, demonstrated superior performance in predicting behavioral outcomes in children compared to traditional models. The DNN effectively captured non-linear relationships within the behavioral data, However, the self-attention mechanism of the Transformer was particularly good at seeing temporal patterns in sequential data. The fusion of both models through a weighted aggregation approach yielded the highest accuracy, with significant improvements in recall and precision.

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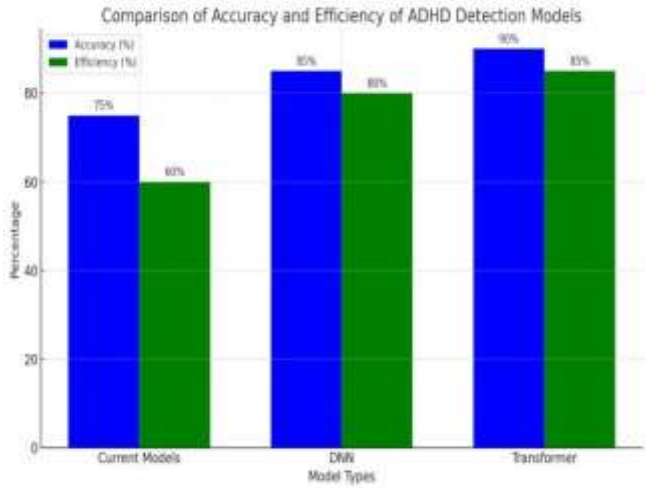

Figure 2. Accuracy and efficiency graph for improved DNN and Transformer based models

Accuracy (A):
A = (TN + TP) * 100 / (TN + FN + FP + FN)

Where,
TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives

Precision (P):
P = (TP * 100) / (TP + FP)

Efficiency (E)
E = (Performance * 100) / (Computational Resources)

Hyperparameter tuning and regularization techniques, such as dropout and L2 regularization, effectively mitigated overfitting, enhancing model generalization. The model's interpretability, achieved through important insights into important behavioral characteristics impacting predictions were offered by SHAP and LIME. Evaluation measures such as ROC-AUC, F1-Score, and Accuracy verified the model's robustness across diverse behavioral categories.
The deployment phase confirmed the model's applicability in realworld scenarios of Figure 2 with consistent performance in both real-time and batch processing environments. Monitoring over time indicated stable performance, with no significant drift observed. The results underscore the potential of hybrid models in advancing predictive modeling for behavioral analysis, offering a reliable and interpretable tool for researchers and practitioners working with children's behavioral data.

VI. CONCLUSION

Although conventional predictive models have yielded significant insights in behavioral research, it is apparent that they are not well-suited for managing intricate, non-linear interactions and high-dimensional data. Transformer-based models and Deep Neural Networks (DNNs) have surfaced as possible substitutes, providing improved capacities to learn from complex behavioral patterns. Even with these advancements, problems remain, especially when it comes to tiny or noisy behavioral datasets. These problems include overfitting, processing needs, and the requirement for large labeled datasets. This research underlines the necessity for combining sophisticated techniques like cross-entropy loss, the softmax function, attention mechanisms, and mean squared error to further develop these models. Future predictive models can enhance the precision and applicability of behavioral predictions by tackling the existing constraints, which will eventually result in improved outcomes for child development monitoring and intervention measures. Further investigation in this area has the potential to revolutionize behavioral analysis by developing more robust and dependable modeling approaches.

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