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Multimodal Neural Network Modelling for ADHD Diagnosis Using Cognitive and Neurophysiological Markers

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Introduction

Attention Deficit Hyperactivity Disorder (ADHD) is a neurodevelopmental condition affecting 5% of children and 2.5% of adults worldwide, with a prevalence that continues to rise. It is characterised by a marked difficulty in attention regulation, emotional regulation, working memory and other executive functions. Despite its significant impact on daily functioning, education, and overall well-being, the diagnostic process for ADHD still heavily relies on subjective behavioural assessments, leading to issues of misdiagnosis, underdiagnosis, and overdiagnosis. The absence of reliable biomarkers for ADHD has long been a major challenge, impeding the objectivity and precision of the diagnostic process.

Problem Statement

ADHD is primarily identified through clinical observations of behavioural symptoms, including inattention, hyperactivity, and impulsivity. These symptoms are inherently subjective and prone to interpretation bias, resulting in considerable diagnostic uncertainty. This subjectivity is compounded by the complex and heterogeneous nature of the disorder, leading to difficulties in distinguishing ADHD from other conditions with overlapping symptoms. The current ADHD diagnosis based on the criteria of Diagnostic and Statistical Manual of Mental disorders(DSM) is mainly based on a subjective evaluation that is subjected to clinician's and reporter's biases and lacks the support of objective indicators. Diagnostic criteria bias may reflect socio-cultural influences on symptom manifestation and diagnostic procedures as well as the substantial overlap between ADHD symptoms and other psychiatric, developmental and neurological conditions (e.g., learning disabilities, depression, anxiety). Consequently, countless individuals may remain undiagnosed, while others may be incorrectly labelled as having ADHD, receiving potentially unnecessary treatments.

Furthermore, the current diagnostic process may not account for the developmental trajectory of ADHD, as symptom presentation can change with age. This further underscores the necessity for an objective, precise, and age-sensitive diagnostic tool that can overcome the limitations of behaviour-based assessments.

The Need for a Computational Marker

To address the problems of misdiagnosis, underdiagnosis, and overdiagnosis in ADHD, we propose the development of a computational marker for ADHD diagnosis. A computational marker offers the potential to enhance the precision, objectivity, and efficiency of the diagnostic process, significantly reducing the reliance on behavioural symptoms and the associated interpretative challenges. Thus, predicting ADHD impairment using objective, easy-to-collect variables by noninvasive methods might be useful as a supportive measure in the evaluation of ADHD and other neurological/psychiatric disorders.

There is a need for reliable diagnostic ADHD markers that can be identified early in life, as early behavioural and developmental interventions for ADHD could improve outcomes. In this study, we aim to propose a method that can effectively identify such potential markers and create a cognitive model for a better diagnosis of ADHD.

How Our Computational Marker Will Help

Our research will leverage the power of neural networks and cognitive models to establish a comprehensive understanding of key cognitive abilities relevant to ADHD. By utilising advanced machine learning techniques, we aim to develop a multi-scale, multi-domain neural network model that can effectively diagnose ADHD by combining cognitive, eye tracking, and EEG markers. This project aims to devise a diagnostic computational model for ADHD by integrating cognitive markers, eye-tracking data, and EEG data through deep learning techniques. This will help in cognitive and neural-marker-based Computer Aided diagnostic (CAD) tools to be implemented in psychiatric healthcare settings.

Objective

- Develop a multi-scale, multi-domain neural network model that can effectively diagnose ADHD by combining cognitive, eye tracking, and EEG markers.
- Utilise Rating scales and Continuous Performance Tests (CPTs) to gather cognitive marker data.
- Collect neurophysiological markers using eye tracking and EEG during the cognitive tasks.
- Train and validate the model to achieve high accuracy and reliability in ADHD diagnosis.

Method

Cognitive Modelling

Cognitive models represent the structures and processes of the human mind, such as memory, attention, perception, and decision-making. This involves defining how information is stored and processed within the model. Cognitive modelling applies knowledge from various domains, including psychology, neuroscience, artificial intelligence, and human-computer interaction.

There are different approaches to cognitive modelling, such as symbolic (using symbols and rules) and connectionist (based on artificial neural networks). In this project, our aim is to build a connectionist deep learning model for diagnosing ADHD since ML models have proved to perform better and had a higher accuracy than the benchmark approach that used clinical data only.

Possible Markers for ADHD

Given the complexity of psychiatric disorders, it is unlikely that a single marker, or even several markers pertaining to the same unit of analysis within a given biological system, i.e., a single domain, will have good enough diagnostic properties to aid real life clinical decisions.
In this study, we propose a *multi domain approach*, using two domains Cognitive Markers - including CPT and Standardised Rating Scales and Neurophysiological markers - eye tracking (measure gaze patterns, fixations and saccades) and EEG data (record data while performing the cognitive tasks to understand neural dynamics) and apply machine learning techniques to these domains to assess their predictability in ascertaining a differential diagnosis of ADHD in individual patients, with sufficient clinical validity and utility.

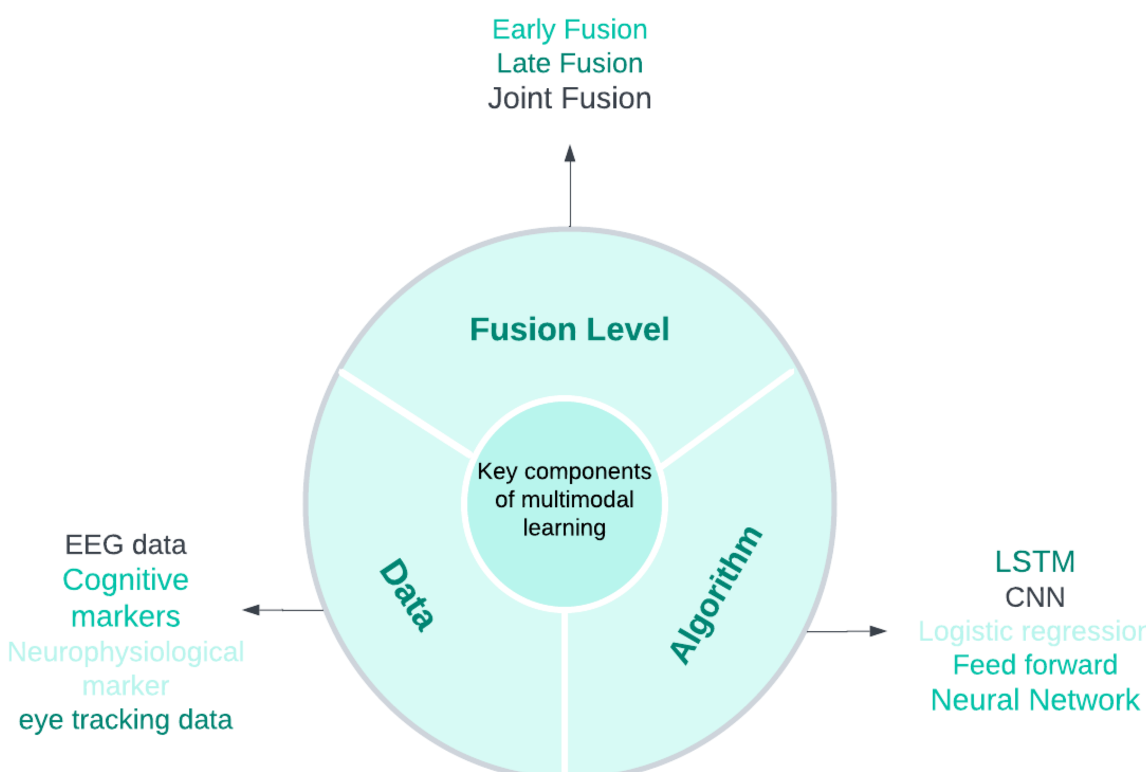
Cognitive markers : Data for cognitive markers can be gathered from various tests such as MOXO - Continuous performance tests (CPTs) which are inexpensive and easy to use, which has resulted in their widespread use for the assessment of cognitive function in suspected ADHD. The MOXO-CPT task requires the child to sustain attention over a continuous stream of stimuli and to respond to a prespecified target. For each child, four CPT indices can be recorded: Attention (number of correct responses to target stimuli, including the rate of omission errors), Timeliness (correct responses to target stimuli conducted on accurate timing), Hyperactivity (a measure of motor activity) and Impulsiveness (responses to non-target stimuli, including the rate of commission of errors). Along with this, other tests such as Wisconsin Card Sort Test (WCST), Delayed discounting (DD) paradigm and Test of Language Development-2 Primary (TOLD-2 Primary) can be used to measure cognitive markers such as working memory, decision making, language processing etc.

Neurophysiological Markers : Neurophysiological markers include tracking eye movement. A recent study 'Use of eye tracking to improve the identification of attention‑deficit/hyperactivity disorder in children' suggests that most eye-tracking indicators (e.g., FR and time, gaze ratio at the centre, and gaze variability) differed significantly between the ADHD and control groups. Along with that, Event-Related Potentials (ERPs) in the electroencephalogram (EEG) also showed robust neurophysiological differences between individuals with ADHD and without

ADHD. Differences in brain structural and functional measures regarding cognitive functions have been reported in patients with ADHD. Hence EEG data and eye tracking data would be two potential markers for the diagnosis of ADHD.
Along with these cognitive and neurophysiological markers, Rating Scales and Personal Characteristic data (PCD) can also be used as joint features.

Creating a Unified Multi-Modal Neural Network Model

Classification of complex behavioural conditions such as ADHD requires a *multi-modal approach*. Multi-modal approach can be seen as a process where multiple parallel channels take multiple inputs, then fuse them into one signal channel to exact combined high-level features, and finally feed the high-level features to a classifier. Here, we propose three models - Recurrent Neural Networks like Long Short-Term Memory (LSTM) networks to handle time series data like EEG data, Convolutional Neural Network (CNN) for eye tracking image data, and Feed forward neural networks for textual data (CPT, Rating scale, PCD etc) to be combined to create a unified multimodal neural network using an approach known as"*Neural Network Fusion*" or "*Multimodal Fusion*." The goal is to create a unified model that can leverage the strengths of each sub-model while capturing the relationships between various data modalities.



Submodel Architecture

Recurrent Neural Networks like Long Short-Term Memory (LSTM) networks
Useful for modelling sequences of data, such as time series data related to cognitive processes. We can utilise LSTM layers to handle the EEG data, which are time series data. LSTM layers can capture temporal dependencies and sequence information in EEG data. In a 2022 study on EEG-based LSTM networks on ADHD, the experimental results indicated that EEG-based LSTM networks produced the best performance with an average accuracy of 90.50 ± 0.81% in comparison with the deep neural networks, the convolutional neural networks, and the support vector machines with learning the cognitive state transition of EEG data.

Convolutional Neural Network (CNN)
Effective for processing and analysing images or spatial data, which might be relevant for certain aspects of cognitive modelling. Implement CNN layers to extract spatial features and process the eye-tracking data, which resembles image data. Can use 2D convolutional layers to extract spatial features from eye-tracking sequences.

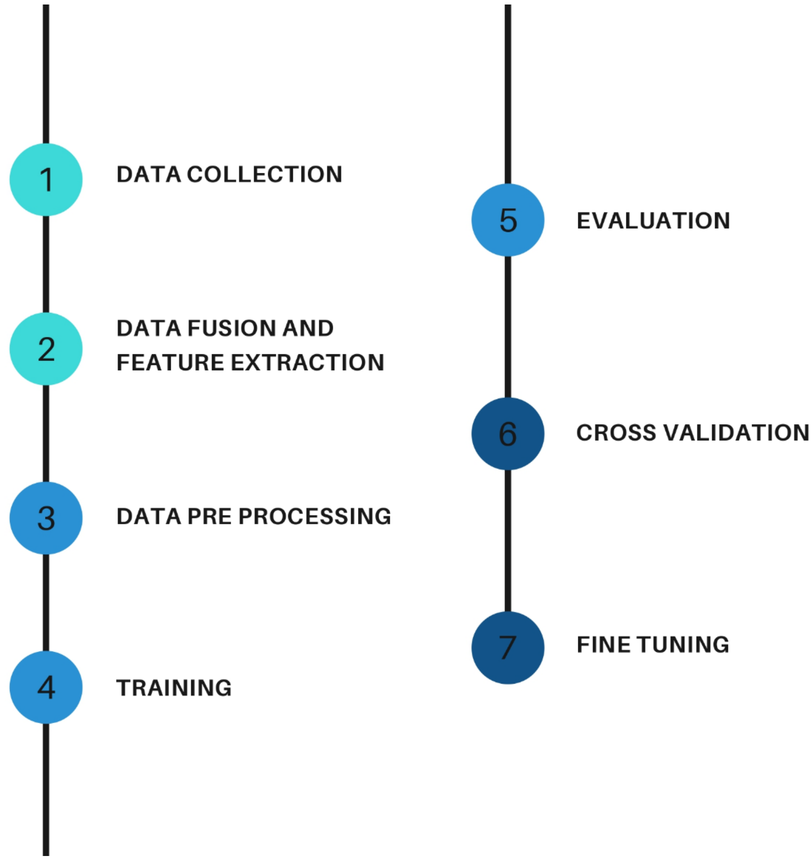
Feed Forward Neural Networks
Finally, for textual data like CPT, Rating Scale, PCD etc. we can use a Feed forward neural network.

How we can build the model

In the first layer, we will collect data from multiple sources including the EEG, eye tracking, CPT and other cognitive markers.

The second layer is the data fusion and feature extraction layer. We will extract relevant features from each sub-model and combine the outputs of the individual modality-specific models into a single feature vector. Various strategies like Early Fusion, Late Fusion or Joint Fusion can be used to fuse the outputs from these sub-models.

A joint fusion approach can be the most well-suited approach for our purpose since it is better at approximating real-world interactions between data points as compared to other approaches.



The third layer in our framework can include data pre-processing that includes tasks like (1) data filtering, removal of duplicate and inconsistent data, and handling missing data; (2) normalisation of multiple types of data distributions between 0 and 1 to make data useable by computational algorithms; (3) feature selection that aims to reduce or eliminate noisy or redundant variables; and (4) feature weighting using conditional probability to improve the predictive accuracy.

Then we intend to train the integrated model with the data and evaluate the combined model's performance in terms of accuracy, sensitivity, specificity, and other relevant metrics to diagnose ADHD accurately. Cross-validation can be implemented to assess the robustness and generalisation of our multimodal model. Finally, we fine-tune hyperparameters to optimise the performance of the combined model.

Expected outcomes

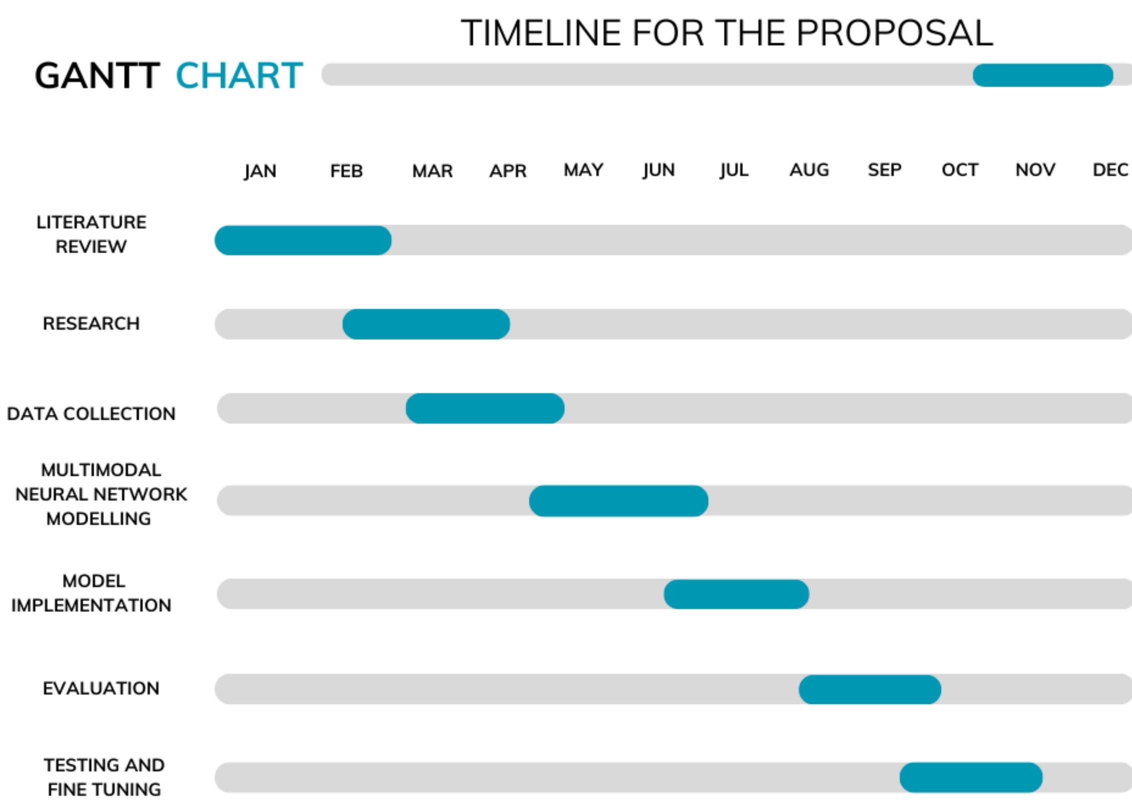
- An easy-to-administer, affordable, non-invasive measure of ADHD-related symptoms.
- A diagnostic computational model with fast discrimination speed and high classification accuracy to make objective predictions for ADHD that outperforms traditional methods.

High sensitivity rates may improve clinicians' ability and confidence in ruling out ADHD. Excluding ADHD when it is not present is very important given the complicated, time-consuming, and expensive process of ADHD diagnosis.
- Insights into the importance of integrating different types of markers for accurate diagnosis.
- Development of a better treatment plan on the basis of more precise diagnosis.
- Foundation for further research in the field of neurodevelopmental disorders.

Ethical Considerations

We will ensure ethical data collection and handling and will make sure to obtain informed consent from participants and protect their privacy.

Timeline



Budget

Eye Tracking Device	30k
EEG Device	170k
Research Participation Incentive Cost	50k
Model Building	50k
Miscellaneous	50k
Total	350k

Conclusion

In this research proposal, we have underscored the pressing need for a computational marker for diagnosing Attention Deficit Hyperactivity Disorder (ADHD) as a solution to the longstanding problems of misdiagnosis, underdiagnosis, and overdiagnosis. The current reliance on behavioural assessments in diagnosing ADHD has proven to be subjective, inconsistent, and prone to interpretative bias. These challenges have far-reaching consequences for those affected by the disorder, potentially leading to inappropriate treatments or the denial of much-needed interventions.

Our proposal seeks to harness the power of cognitive modelling and neural networks to construct computational markers that objectively measure key cognitive abilities relevant to ADHD. This innovative approach aims to significantly enhance the precision and accuracy of ADHD diagnosis, addressing the limitations of the current behavioural symptom-based assessment process.

The potential impact of our research is vast. By improving objectivity and reducing the risk of misdiagnosis, our computational markers have the potential to transform the lives of individuals with ADHD. The markers will also support early diagnosis, allowing for timely and targeted interventions, thereby enhancing long-term outcomes and reducing the associated societal and personal burdens.

Moreover, our research will pave the way for a more age-sensitive understanding of ADHD, recognizing the evolving nature of symptom presentation across the lifespan. This adaptability to developmental changes is a key feature of our computational marker, setting it apart from traditional diagnostic methods and better addressing the complexities of ADHD.

In summary, this research proposal represents a significant step forward in the field of ADHD diagnosis. The introduction of computational markers will not only alleviate the issues of misdiagnosis, underdiagnosis, and overdiagnosis but also foster greater confidence in the diagnostic process. As we embark on this research journey, we anticipate transformative outcomes that will ultimately improve the quality of life for individuals with ADHD, ensuring that they receive the precise care and support they need. Our endeavour aligns with the broader vision of advancing the field of mental health diagnostics and exemplifies the potential of cutting-edge technology to positively impact the lives of those facing neurodevelopmental challenges.

References

1. Baltrusaitis, T., Ahuja, C., & Morency, L.-P. Multimodal Machine Learning: A Survey and Taxonomy.

2. Børglum, A. D. Genome-wide analyses of ADHD identify 27 risk loci, refine the genetic architecture and implicate several cognitive domains. Nature Genetics

3. Chang, Y., et al. (2022). Neurological state changes indicative of ADHD in children learned via EEG-based LSTM networks. J. Neural Eng., 19(1), 016021.

4. Chen, M., et al. (2019). A Multichannel Deep Neural Network Model Analysing Multi Scale Functional Brain Connectome Data for Attention Deficit Hyperactivity Disorder Detection. Radiology: Artificial Intelligence, 2(1), e190012.

5. Fernandes, et al. (2020). Precision psychiatry with immunological and cognitive biomarkers: a multi-domain prediction for the diagnosis of bipolar disorder or schizophrenia using machine learning. Translational Psychiatry, 10, 162.

6. Groves, N. B., et al. (2022). Executive Functioning and Emotion Regulation in Children with and without ADHD. Res Child Adolesc Psychopathol, 50(6), 721–735. doi:10.1007/s10802-021-00883-0.

7. Lee, D. Y., et al. Use of eye tracking to improve the identification of attention-deficit/hyperactivity disorder in children. Nature journal.

8. Loh, H. W., et al. (2023). Deep neural network technique for automated detection of ADHD and CD using ECG signal. Computer Methods and Programs in Biomedicine journal.

9. Moghaddari, M., et al. (2020). Diagnose ADHD disorder in children using convolutional neural network based on continuous mental task EEG. Computer Methods and Programs in Biomedicine, 197, December 2020.

10. Qiu, S., et al. Multimodal deep learning for Alzheimer's disease dementia assessment. Nature Communications.

11. Rahaman, M. A., et al. Deep multimodal predictome for studying mental disorders. Wiley.

12. Takács, Á., Kóbor, A., Tárnok, Z., & Csépe, V. (2014). Verbal fluency in children with ADHD: Strategy using and temporal properties. Child Neuropsychology, 20(4), 415-429. DOI: 10.1080/09297049.2013.799645.

13. Wang, C., et al. (2022). Towards high-accuracy classifying attention-deficit/hyperactivity disorders using CNN-LSTM model. J. Neural Eng., 19(4), 046015.

14. Montavon, G., et al. Methods for interpreting and understanding deep neural networks. Digital Signal Processing, Volume 73, Pages 1-15.

15. The Neuro Bureau ADHD-200 Preprocessed Repository - http://preprocessed-connectomes-project.org/adhd200/.