Computer Game–Based Detection of ADHD in Adolescents

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***Abstract*—Attention Deficit Hyperactivity Disorder (ADHD) is a neurodevelopmental condition that affects attention, impulse control, and working memory. Diagnostic methods mainly rely on clinical interviews and self-reported questionnaires. As such, they are subjective, often lacking objectivity and controlled assessment methods. This paper discusses a computer-based framework using a gamified approach for screening ADHD through two interactive cognitive tasks: the Alien Defense Simulator (Go/No-Go) and the 1-Back Challenge (N-Back). Implemented in Python and Pygame, the stated games objectively assess sustained attention, responses inhibition, and working memory while promoting user engagement; without the user needing to specify ADHD symptoms. Moreover, real-time data is logged from users and includes behavioral metrics including accuracy, reaction times, omissions, and commissions which are mapped to the cognitive domains of ADHD. Extracted features are statistically analyzed and undergo supervised machine learning modelling (logistic regression and decision tree classifiers) to identify the patterns that describe ADHD. The preliminary findings indicate the proportion of commission errors, variability in reaction times, and accuracy decline from a lower to a higher performance on the gaming tasks when a user reports attentional difficulty. The proposed system outlines an objective method consisting of video games for the scalable screening of ADHD with participatory engagement as an alternative to conventional clinical interview style assessments while informing early detection in educational and clinical settings.**

***Keywords*—*Attention Deficit Hyperactivity Disorder (ADHD), Cognitive assessment, Gamification, Go/No-Go task, N-Back task, Reaction time analysis, Impulse control, Working memory, Machine learning classification, Pygame implementation.*

I. INTRODUCTION

Attention Deficit Hyperactivity Disorder (ADHD) is a common neurodevelopmental disorder that involves children and adolescents showing deficits in attention, impulsivity, and hyperactivity. The impairments from ADHD create major issues for academic performance, socializing, and overall quality of life. Although diagnosis is primarily made via clinical interviews, and subjective and potentially biased rating scales, there is a general lack of consistency and

absence of valid performance based measures. There is a need for effective screening; it is a screening tool or a screening instrument that is quantitative, reproducible, and scalable.

Cognitive neuroscience has demonstrated that the Go/No-Go task and N-Back task (next level up in complexity) can add significantly to our ability to effectively measure the executive functions most likely blocked in ADHD. Go/No-Go requires sustained attention across repeated trials, sustained inhibition of responses, sustaining the ability to switch between tasks if needed, while the N-Back is primarily asked to switch tasks and utilize working memory. By making the current cognitive paradigms more interactive and gamelike, we create more interesting user experiences, while allowing us to accurately collect behavioral data. Recent studies have highlighted that computer-based cognitive assessments have great utility and offer real-time data on attentional control, impulsivity, and memory processes, all vital and major markers of ADHD.

This paper describes the design and implementation of two gamified cognitive tasks, the Alien Defense Simulator (Go/No-Go) and the 1-Back Challenge (N-Back), using Python and Pygame. The system measures performance by collecting metrics related to accuracy, reaction time, omission errors, and commission errors and relating these metrics to cognitive domains related to ADHD. Statistically, and by use of supervised machine learning constructs to derive meaningful class between participants based on behavior. The major contributions of this work are:

1. To provide an appropriate reasoning and engaging tool for a game-based and engaging ADHD screening assessment.
2. To provide a real-time behavioral recording system where the task difficulty was adaptive supporting better task sensitivity.
3. To provide machine learning to improve sensitivity for risk prediction in ADHD.

This study represents an attempt to integrate established cognitive paradigms with an interactive design to create an ADHD screening tool that is objective, data-driven and relevant to existing testing paradigms. By demonstrating that an engaging gamified version of ADHD screening may achieve value-added word rather than being additive in nature, the study aims to be used alongside traditional diagnostic approaches, with possible use in educational or clinical practices.

II. Literature Review

The study conducted by **Zakani Zeinab et al. [1]** aimed to facilitate the overcoming the difficulty of large-scale screening of Attention Deficit Hyperactivity Disorder (ADHD) and the need for objective early identification. To accomplish this, the researchers validated FishFinder, a novel machine learning-based video game which measures attention, impulsivity, and hyperactivity in children aged 5-12 years using performance while playing the game, and using smartphone based motion sensors. This study was conducted on 52 children (26 ADHD, 26 controls) and the results demonstrated high accuracy with an overall performance of 92.3%, sensitivity of 90%, and specificity of 93.7%. FishFinder's performance was either superior or equivalent to other currently available assessment methods and provided a more engaging and less threatening assessment experience for children. There were limitations associated with this study, including use of medicated participants and diversity of ages and gender. For future work, it would be best to use untreated groups and incorporate all age and gender groups in the diversity of the sample. In summary, FishFinder is an efficient, accessible, and fun tool for screening ADHD.

Lee Wonjun et al. [2] proposed a child-friendly ADHD screening game was developed, in which skeleton data were collected using multiple Azure Kinect depth sensors while children simulated the path of a robot. The data were categorized into types of ADHD, ADD-RISK, and normal behavior using deep learning models, with the model of choice delivering the best accuracy of 97.82% with bidirectional LSTM. The results identified children within the ADHD-RISK category, which is an important and complex clinical category. The system also demonstrated that ADHD behavior could be objectively measured by skeleton movement patterns, providing an exciting non-invasive and scalable solution to screening for ADHD outside of clinical settings.

Wiguna Tjhin et al. [3] proposed a four-part mixed-methods model for designing a VR-based ADHD diagnostic game that integrates deep learning (DL). VR offers an immersive and playful atmosphere, which lowers anxiety levels and captures the components of inattention, impulsivity, and hyperactivity better than conventional neuropsychological measures. DL models produce better, faster, and more accurate feature extraction and predictive diagnoses; in particular, convolutional neural networks have provided the best results. The attention to mixed-method approaches was significant in terms of advancing past diagnosis, and aiding reliable and applicable diagnostics especially in lower resourced environments that offer tele-consultation. The VR-DL tool was proposed as future-oriented, sensitive and specific to identify ADHD in children.

Santos Fabio EG et al. [4] examined the potential of the Supermarket Game, a computer-based cognitive assessment directed toward supporting ADHD diagnosis. The students, 80 in total, played 18 levels in the game and were previously categorized by their teachers using DSM -IV criteria. Player data consisted of points scored and time spent on each level and was analyzed using naïve Bayes and decision trees classifiers. The analysis showed categorical attributes provided better results when compared to numeric scanned attributes, some features were identified to produce the best classification results through feature selection. Supermarket Game exhibited good sensitivity in identifying children who were ADHD-positive, but had challenges differentiating ADHD subtypes. The authors concluded that the game-based behavioral data on ADHD, in collaboration with machine learning could replace the reliance of subjective reporting and provide more objective diagnostic assessment.

Delgado Gómez et al. [5] examined Running Raccoon, an infinite-runner video game designed to objectively assess inattention in children with ADHD. The game assessed omissions and jumping timing, to identify attentional control, and compared these with caregiver rating of inattention. The 32 children were aged 8-16 and medicated. The performance metrics showed significant correlation with ADHD symptom severity, with stronger results observed at longer inter-stimulus times. The pilot examination revealed the potential for small, enjoyable, and ecologically valid games to assess ADHD. However, the limitations of small sample size, those already on medication, and the absence of a contact group noted. Overall, Running Raccoon provided preliminary support for simple, available games to be used objectively as a task for screening and monitoring ADHD.

Madeleine J. Groom et al. [6] explored how computer games have the potential to facilitate monitoring and treatment of Attention Deficit Hyperactivity Disorder (ADHD) by stimulating users while evaluating or practicing cognitive functions. The authors pointed to existing games which include attention, working memory, inhibitory control; and the trials employed in a Go/No-Go or Stop–signal tasks paradigm, or games which used biofeedback and brain-computer interface (BCI) for self-regulation. The authors also presented prototypes, SnappyApp, Awkward Owls, and Wormy Fruit, designed to monitor behaviors associated with ADHD and provide therapy in a playful manner. The authors conducted pilot studies that suggested engaging users and promoting a greater awareness of their symptoms, but there were issues with validation, maintaining user motivation, and sameness and standardization of outcome measures. The authors concluded there is good potential for using computer games for monitoring and therapy for ADHD, but recommended clinical validation should still be determined.

Lee Wonjun et al. [7] proposed a novel robot-led screening game, using skeleton data and a bidirectional LSTM with channel attention (in other developments this could mean up to 2000) to classify children into three groups: ADHD, ADHD-RISK, and normal. The game was conducted in child-familiar and friendly environments, such as schools; children were more relaxed, and acted in a way that maximized natural behaviors. From the results, an impressively high accuracy of 98.15% was achieved, but the attention scores also indicated that the later stages of gameplay were the most informative for ADHD-RISK group detection. As opposed to previous literature considering ADHD vs. normal, this study distinguished the clinical implications of adding the ADHD-RISK group along with the objective, engaging, and scalable screening pathway for pre-empt intervention for ADHD.

da Costa et al. [8] examined cognitive performance in twenty students aged 8-14 years (10 ADHD, 10 controls) using WiMind, a BCI and digital game based on the Stroop Test. EEG was used to capture participants' brain signals, the brain signals were processed for feature extraction which was used in turn to provide neurofeedback. Statistically significant differences in cognitive performance were observed with non-ADHD students exceeding those of ADHD students in eight out of nine measures of cognitive performance. Interestingly, ADHD participants were observed to have improved performance across all three phases of the game, suggesting a potential therapeutic application. The study concluded that BCI combined with gamified cognitive tasks provides a reliable and enjoyable means of both differentiating students with ADHD from their non-ADHD peers, in addition to facilitating cognitive training.

Almudena et al. [9] examined GokEvolution, a neurofeedback game, in conjunction with a portable NeuroSky MindWave EEG headset, to measure attention levels in children with Attention Deficit/Hyperactivity Disorder (ADHD) using signature EEG metrics. Seventy-five children (n =52 control subjects, n= 23 ADHD) aged 7 – 12 years participated in the research. EEG attention metrics were taken as the children played the game and results were compared to standardized (CARAS-R) psychological test scores. Children with ADHD had significantly lower attention scores and a significantly more variable indication of EEG responses. The combined system was successful in measuring low attention profiles for all subjects and distinguishing levels of attention in children endeavoring the task versus those that abandon the task. Collectively, the results indicate that the measurement system may serve as a low-cost and noninvasive clinical screening tool to measure attention levels in children for the early detection of attentional deficits.

María et al. [10] tested two cognitive interventions - The Secret Trail of the Moon (TSTM), a VR-based chess serious game, and Therapeutic Chess (TC) - as adjuncts to medication treatment in clinically stable patients with ADHD (n=105, aged 12-22). Patients were randomly assigned to one of three groups (TSTM, TC, control) for a 12-week treatment period. Although there were no statistically significant improvements to the overall executive function index (BRIEF-2), the TSTM and TC groups both demonstrated improvements in areas related to both emotional regulation and inattentiveness. The TSTM group also demonstrated improvements in functional context at school. While results should be considered exploratory, the present study provides evidence and support for expanding tested game-based cognitive training as an adjunct ADHD intervention - larger studies appear warranted.

Leonardo Becheri et al. [11] examined 20 studies on the comorbidity of ADHD and Gaming Disorder (GD) in individuals aged 0-18. The review highlighted a high prevalence of problematic gaming in children with ADHD ranging from 29% to 83.3% and found that ADHD symptoms were strongly associated with severity of GD. The studies included in the review utilized numerous diagnostic tools (YIAS, CIAS, IAT, IGDI, GAIT) to assess GD. Neuroimaging studies demonstrated altered functional connectivity between the cortex and caudate in the ADHD+GD group that was improved following treatment. The paper identified the need for standardized diagnostic tools, as well as early screening and interventions that addressed not only ADHD symptoms but also problematic gaming behaviours.

Nicolás et al. [12] proposed Attention Slackline - a serious game aimed at measuring ADHD symptoms in children and adolescents - was validated. A total of 71 participants (32 ADHD, 39 controls) completed the Attention Slackline game, divided into children (6-11) and adolescents (12-17). The results indicated significantly poorer performance on the Attention Slackline among children with ADHD compared to the controls, and performance was negatively correlated with hyperactivity/impulsivity symptoms, whilst there was no significant difference among adolescents. The tool had strong discriminative ability for children, but only limited validity for adolescents; likely due to developmental considerations. In conclusion, Attention Slackline was demonstrated to be an engaging, objective, and age-sensitive tool to measure hyperactivity/impulsivity in children with ADHD.

Choon Guan et al. [13] evaluated a BCI-based attention training game system for non-medicated children with ADHD. Twenty participants (16 boys, 4 girls, 6-12 years old) wore a headband containing dry EEG sensors to monitor their attention levels while playing a feedback-based game over eight weeks, with follow up booster sessions. Significant improvements were identified in inattentive and hyperactive-impulsive symptoms with large effect sizes that maintained until 24 weeks. The EEG-based changes in ADHD severity corresponded with behavioral improvements, supporting neurological mechanisms of action. The BCI-based game system demonstrated preliminary evidence of being a non-medication alternative to treat ADHD.

III. METHODOLOGY

This section describes the design, implementation, and analysis process for the proposed gamified ADHD detection approach. The methodology is presented in a systematic manner, starting from the development of the game, acquisition and treatment of the data, cognitive mapping, and predictive modeling. The methodology can accommodate cognitive psychology, computer science, and machine learning to ensure each step develops an objective, consistent, and scalable screening tool.

A. Game Architecture Overview

The system design has two core game modules using existing neuropsychology paradigms: Go/No-Go task and N-Back task. These games are designed to measure areas of executive functioning that typically are not working well and/or in tandem with others in kids with ADHD, namely: response inhibition, sustained attention, and working memory.

Game 1: Alien Defense Simulator (Go/No-Go): This game will measure impulsivity and attentional control of participants as they are required to respond to "Go" stimuli (red alien ships) as well as refrain from responding to "No-Go" stimuli (green alien ships). Because this paradigm will exist in a fast-paced arcade style format, the system will maximize the likelihood of engagement whilst measuring both impulsive and inhibitive responses as shown in Figure.1.

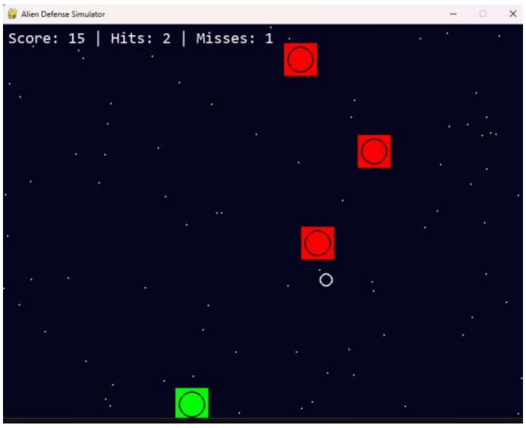

Figure.1: Alien Defense Simulator

Game 2: N-Back Challenge (Working Memory): This game will assess working memory and cognitive flexibility by requiring the participant recall and compare sequences of letters and sequences of positions. The system will adaptively increase the N-level based on performance, which will be a controlled cognitive stressor to provide a more sensitive measure of managing memory load as shown in Figure.2.

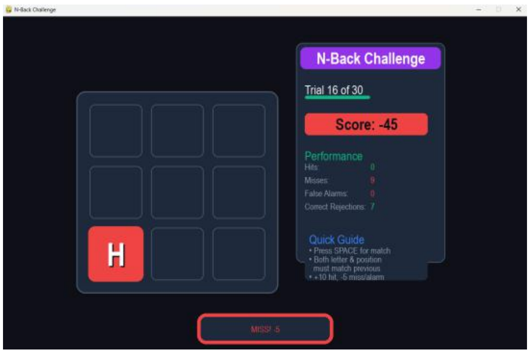

Figure.2: N-Back Challenge

Technical Implementation: Both games are programmed in Python with the Pygame library because it allows for:

- Real-time rendering: Allows for a smooth and enjoyable experience.
- Accurate event handling: Allows for tracking mouse and keyboard responses with high resolution.
- Timing control: Allows for timing the measurements of reaction time to the specific millisecond, which is a neuropsychological necessity.
- Audio-visual feedback: Provides background music, sound effects, and animations to replicate real-life distractions.

The game is designed using a modular coding style. There are separate modules for stimulus presentation, event detection, logging responses and data export. This will help with debugging, allows for scaling the distance game, and perhaps in the future, extensions to mobile versions or add other tasks that are cognitive in nature.

B. Gameplay Design and Objectives

Alien Defense Simulator (Game 1: Go/No-Go)
Objective: The player must shoot red alien ships ("Go" targets) that drop down, while not shooting green alien ships ("No-Go" targets) that drop down. Any omission or commission will be logged as an error.

Cognitive Rationale:

1) Sustained Attention: Ability to sustain attention over multiple waves of stimuli.
2) Impulse Control: Ability to withhold responding without a target.
3) Processing Speed: Ability to measure processing speed for valid responses.

Adaptive Difficulty: The frequency of alien spawns and the speed of descent increases, requiring constant adaptations of attentional effort and inhibitory control.

Data Collected:

1) Total score for each session
2) Number of correct hits and misses
3) Commission errors (impulsive choice to "No-Go" responses)
4) Reaction times at each trial
5) Accuracy percentage
6) Start and end time stamps for determining session time

2.1 N-Back Challenge (Game 2: Working Memory)

Objective:

- The goal of the exercise is for players to shoot the alien ships as they descend (Go stimuli) before they reach the bottom of the display.

- Players must also refrain from shooting the green alien ships (No-Go stimuli) as they represent trials of inhibitory control.

Gameplay Mechanics:

1. Red alien = Target (response is time critical)
2. Green alien = non-Target (inhibition of response is required)
3. Players will aim and shoot using either a mouse or keyboard.
4. Level of difficulty increases as the spawn and speed of the aliens rises over the duration of play.

Cognitive Targets:

Sustained Attention:

- Players are required to continuously monitor multiple moving targets.
- Participants will sustain attention over the course of multiple consecutive waves.

Impulse Control:

- When players see non-targets they must inhibit their response to fire when they see the green aliens.
- Prevent participants from being "trigger-happy."

Motor Response Speed:

- Players aim quickly, and respond to shoot accurately.
- Reaction time will be measured in milliseconds.

Data Captured:

1. Number of hits (correct responses given to red aliens).
2. Number of 'misses' (failing to shoot red aliens).
3. Commission errors (incorrectly responding to green aliens).
4. Reaction time per action (valid).
5. Session-level metrics: accuracy percentage, player score, timestamps.

2.2 N-Back Challenge (Game 2: Working Memory)

Objective:

- Display a series of letters in a 3x3 grid.
- The player will hit the space bar if the letter in the grid displayed is a 'match' with the letter N steps displayed previously in the same location in the grid.
- The player will do nothing if there is no match.

Game Mechanics:

1. Stimulus = letters appear at random location on a grid.
2. Starting difficulty: N = 1 (1-back).
3. Dynamic difficulty:
   a. If accuracy > threshold → N increases (e.g., 2-back, 3-back).
   b. If accuracy < threshold → N decreases.
4. Time stimulus on the screen decreases at increased difficulty.
5. Distractor flashes mimic attention challenges in real-life situations.

Cognitive Targets:

Working Memory:

- Hold information in working memory for N steps.
- Be able to replace those steps with new information.

Selective Attention:

- Ignore distractor flashes/distractors in the background.
- Pay attention to letters–position sequences only.

Cognitive Flexibility:

- Change mental tactics as task difficulty increases.
- Change from short-term recall (1-back), to longer-term recall (2-back or 3-back recall).

Data Captured:

1. N value used in each trial.
2. Hits (correct detections of the N-back match).
3. Misses (failed to detect a match).
4. Commission errors (false positive detections).
5. RT per trial.
6. Accuracy per session.
7. Documentation of timing of start, stop for session.

C. Data Logging and Storage

Recording data accurately and reliably is vital for the translation of gameplay interactions into meaningful cognitive metrics. Both games record every user action and system event in real-time using a structured data logging system that stores data in CSV (Comma-Separated Values) files in order to ensure data integrity and reproducibility (the materials that offer, for example, option A for gameplay A and option B for gameplay B will be available). Using the CSV format offers platform independence and creates a file type that is accessible in common statistical and machine learning software (e.g., SPSS, R, MATLAB, and Python [e.g., Pandas, Scikit-learn]).

3.1 Logged Parameters

The logging system allows for the measurement of a variety of parameters. We will review these parameters, which are generally categorized in terms of:

Performance Metrics: Player score, resulting from the points assigned at the end of each session. Accuracy rates, which are the proportion of correct responses relative to total trials. Counts for both correct and incorrect responses to allow researchers to profile errors, as they can be included in a deep error analysis model.

Importance: The traceable and quantifiable value of success and failure in cognitive capabilities tasks and their respective accuracy is a key feature of the serious game design of both games.

Temporal Data: Reaction times (RT's), in milliseconds, for every trial. Session total time (the time that the participant starts the task to the time of the conclusion of the task). Duration of prompts/stimuli (the time stimuli are on the screen).

Importance: Reaction times (RT's) and the variability of RT's are considered some of the strongest behavioral markers of ADHD, and are indicative of difficulties in behaviors like inattention, e.g., consideration of all possible responses before selecting one or poor speed consistency.

Difficulty Progression: Spawn rate and movement speed of aliens in the Go/No-Go task. N-value (1-back, 2-back, etc.) and presentation duration in the N-Back task.

Importance: Facilitates observation of how participants adjust to an increase in cognitive load, both in terms of endurance and flexibility.

Behavioral Indicators: Premature responses (responses prior to the full presentation of the stimulus). Missed trials (non-response to targeted stimuli). Trends toward consistency throughout the session (e.g., fatigue type effects, learning type effects).

Importance: Captures impulsivity (false alarms), lapses of attention (misses), and the stability of performance data - all important indicators for screening ADHD.

3.2 System Features for Reliability

The logging system has several safety protocols in place to optimize the collection of high-quality data.

Non-Redundancy: The header (aka column names) for the CSV is written only once at the beginning of each file. This eliminated the need for writing the same header name in multiple sessions when appending all sessions. An important feature for providing clean input into downstream statistical and machine learning models.

Traceability: Each log file name encodes critical metadata including participant ID, date, and time of the session. This also allows research teams to track longitudinal data from the same participant across multiple sessions. Which is critical for data integrity and reproducibility of the experiments.

Scalability: The logging schema is vastly extensible and will allow more parameters like physiological data and eye-tracking measures to be easily added without having to change its structure. Provides support for integrating with multi-modal data sources in anticipated future versions of the project.

3.3 Relevance to ADHD Detection

The logging framework functions to transform raw gameplay into structured datasets that can correspond to cognitive functions related to ADHD:

- High variability in reaction time: measure of attentional lapses.
- Frequent commission errors: measure of impulsivity.
- Increased miss rates at increased difficulty: measure of working memory.
- Diminished consistency in performance comparisons: measure of sustained attention.

Thus, the logging and storage mechanism can be viewed as more than just a technical component; it is at the heart of the cognitive evaluation pipelines, and scientific standards can be applied to the statistical analyses and machine learning classifications established on the data.

D. Cognitive Parameter Mapping

The raw gameplay metrics collected from the two interactive tasks do not directly reflect cognitive constructs; therefore, a structured mapping process is necessary to convert in-game parameters into clinically significant cognitive neuroscience parameters for ADHD. This mapping process lends scientific legitimacy to the proposed framework by ensuring that all recorded parameters can be interpreted in relation to established benchmarks in psychology.

4.1. Attention Span
The capacity to focus on and maintain concentration on relevant stimuli over an extended period, even in the presence of distractions or repetitive nature of tasks.

Game Mechanics:

- Alien Defense Simulator: Sustained accuracy percentage across multiple waves with increasing spawn rates of aliens.
- Sustained hit rate consistency over extended gameplay.
- Sustained accuracy with challenging levels, which is interpreted as diminished capacity for sustained attention.

Relevance to ADHD: Generally, people with ADHD present an inability to sustain attention or have lapses in attention, and they fail to maintain consistent performance during an extended task or activity, especially as task demands increase. A downward trend in accuracy over time is a clinical corroboration: active attention span is diminishing.

4.2. Impulsivity
The tendency to act without the proper deliberation resulting in responses that are either premature or inappropriate.

Game Mechanics:

- Alien Defense Simulator: Commission errors (or "No-Go" aliens) indicate impulsive errors.
- Premature firing before the stimulus is fully presented to the participant.
- The frequency of false alarms is initial evidence of impulsive decisions that exceed appropriate levels of incorrect detection within the study.

Relevance to ADHD: Impulsivity is a key characteristic of individuals with ADHD. A high count of commission errors indicates problems with inhibition related to dysfunction in the regulation of the prefrontal cortex, representing a specific marker for inhibitory control issues.

4.3 Working Memory
The ability to store and manipulate information for brief periods while executing cognitive tasks.

Game Mechanics:

- N-Back Task: The percentage of accurate responses to letter-position pairs on each N-level (e.g., 1-back, 2-back).
- Performance will decline on the matching task across N-levels, demonstrating that working memory has limitations.

Relevance to ADHD: Deficits in working memory are a well-established finding within the ADHD literature. The ability to maintain accuracy across the N-levels is an indication of the capacity to manage increased cognitive load, which directly relates to difficulties in problem-solving both academically and in real life.

4.4 Processing Speed
The speed at which one can perceive stimuli, process the information, and respond to stimuli.

Game Metrics:

- Mean reaction time (RT) will be measured across trials.
- Intra-individual variability of RTs (i.e., standard deviation across correct responses).
- Slow or inconsistent responses were recorded in both Go/No-Go and N-Back.

Relevance to ADHD: Higher variability in reaction time is a defining characteristic of ADHD and is indicative of lapses in attention, slowing of cognitive processing, or motor responses that lack consistency. Measuring the average time and response time variability describes the entire track of efficiency of processing.

4.5 Parameter Integration

By examining these four cognitive domains, the system generates a multidimensional behavioral profile for each participant:

- Attention Span: reflected in the amount of time that the participant is involved.
- Impulsivity: inhibition control.
- Working Memory: load of information.
- Processing Speed: efficiency and consistency of cognition.

This mapping will enable raw data during gameplay to be transformed into clinically relevant features and will allow the framework to function as a reliable ADHD screening tool.

E. Evaluation and Analysis Pipeline

The unrefined gameplay information elicited from the two cognitive tasks go through a sequentially defined analysis pipeline. This analysis pipeline allows the information logged during the sessions to be analyzed, modified, and converted into clean, relevant, and predictive features for ADHD detection. The pipeline has four major steps: Preprocessing, Feature Extraction, Statistical Analysis, and Machine Learning Modeling.

5.1 Preprocessing

Raw CSV files are first aligned to eliminate discrepancies and prepare the dataset for analysis. The preprocessing pipeline consists of:

Reaction Time Alignment

- The reaction times (RTs) are processed in milliseconds.
- Values are then recast into numerical and/or arrays for statistical and computational processing.
- Assures equality across participants and trials.

Response Recoding

- Verbal based responses (correct, incorrect) are coded to reflect a binary flag (1 = Correct, 0 = Incorrect)
- Provides compatibility with statistical tools, including algorithms that require supervised learning.

Outlier Filtering

- Unreasonably fast responses (<100 ms) would be removed as these are likely anticipatory guesses made by participants.
- Unreasonably slow responses (>2000 ms) are discarded to preserve the potential for distraction or disengagement from the task.
- Outlier removal adds robustness to mean and variance.

Normalization

- Data attributes including RT, accuracy, and error rates are scaled to comparable ranges.
- Prevents machine learning indices from being biased by data attributes that are numerically larger initially.

5.2 Feature Extraction

The cleaned dataset yields domain-specific features that lend themselves to assessing cognitive performance.

Go/No-Go task features:

1. Hits - Correct responses to the red "Go" stimuli.
2. Misses - Failures to respond to "Go" stimuli.
3. Commission errors - Incorrect responses to the green "No-Go" stimuli (impulsivity).
4. Hit and miss rates - Proportions that measure accuracy versus inattention.
5. Mean reaction time (RT) - The average latency of responses.
6. RT variability - Standard deviation of the RTs that reflects attentional consistency.

N-back task features:

1. Hits - Correct detections of N-back matches.
2. Misses - Misses-valid match detections that were valid.
3. Commission errors - False positives during non-matching trials.

4. Hit and miss rates - Accuracy rates across increasing N-levels.
5. Mean RT - A measure of response speed across the N-back conditions.
6. RT variability - Stability of performance, as a function of increasing memory load.

5.3 Statistical Analysis

To assess differences at the group-level between ADHD and control participants we will utilize the following statistical methods:

t-tests and ANOVA: These will be used to compare mean reaction times, error rates, and accuracy metrics across groups. For example, ADHD participants may show a significant difference in terms of slow response time (RT) or commission errors.

Reaction Time Distribution Analysis: The shape of the RT distribution is analyzed, in addition to mean RTs. ADHD participants displayed higher intra-individual variability, meaning the responses across trials were shown to be less reliable among ADHD participants.

Effect Size Computations: Cohen's d and eta-squared will be calculated to determine the magnitude of the group difference.

5.4 Machine Learning Modeling

Supervised machine learning models will be used to establish predictive power based on the derived features.

Input Features:

- Mean and variability of the reaction times.
- Hit/miss rates.
- Commission errors.
- % accuracy.

Algorithms:

1). Logistic Regression:

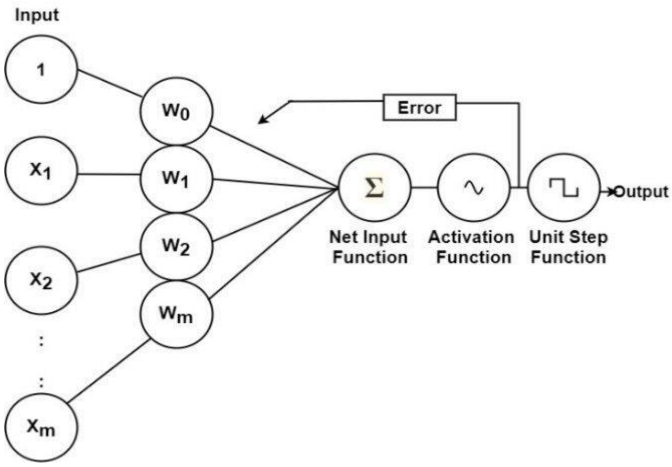

Figure3: Perceptron model for binary classification

Figure.3 shows the layout of a perceptron-based model in which multiple inputs are each multiplied by their weights and the results of the multiplication are added to a bias term (if used) to yield a weighed sum or net input. This net input is then passed through an activation function, after which the activation function output with or without the bias term is passed through a threshold or unit step function to create an output (usually worth zero or one). If the output differs from the known/delivered label, an error signal is produced and used to make weight updates in a repetitive fashion. This produces the learning from the data and is at the root of logistic regression and neural networks for classification purposes.

2). Decision Trees:

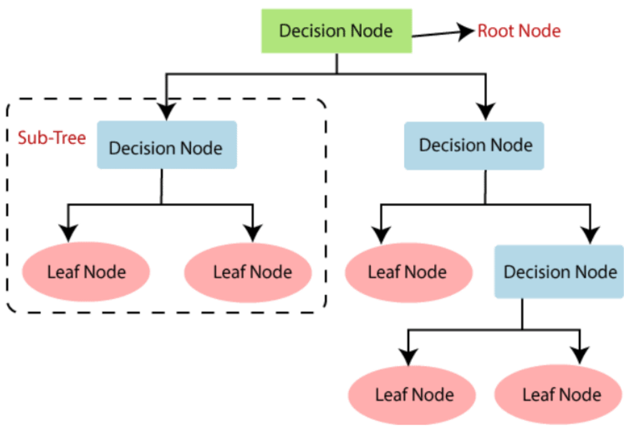

Figure 4: Decision tree structure for classification.

Figure.4 shows the design of a decision tree, which is a supervised learning model where predictions are produced from data representation by partitioning the data into branches that are created based on the defined conditions of the features. A decision tree begins with the root node that describes the main decision and, thereafter, the decision nodes continue to partition the data until a terminal leaf node that describes the predicted outcome is reached. The sub-tree are the decision tree sections, smaller parts of the bigger decision tree, the decision tree describes a hierarchical order that is essentially intuitive, clear, and easily processed when used for classification or regression.

Evaluation Metrics:

1. **Accuracy:** Overall proportion of cases that were classified correctly.
2. **Precision/Recall:** Deals with the false positive/false negative balance which is especially important when screening for ADHD because misclassified cases may impact diagnosis.
3. **ROC-AUC:** Assesses the model's discriminatory ability independent of a chosen threshold.

Cross Validation: The data will be divided into training and test folds. It allows for generalizability estimates of the model to unseen participants. It prevents the model from overfitting to a small dataset.

IV. RESULTS

The assessment of participant performance across both interactive games yielded nuanced understanding of cognition applied to ADHD and the benefit of an integrated system to capture behavioral indicators across a number of complex and overlapping cognitive domains, such as sustained attention, impulse control, working memory and processing speed.

A. Go/No-Go Task (Alien Defense Simulator)

The Go/No-Go task produced measurable behavioral indicators of attention control and inhibitory functioning. Specifically, participants achieved moderate hit rates in the No-Go condition, but experienced elevated commission errors that indicated impulse control issues and/or lapses in response inhibition. Additionally, there was a high variability of reaction times suggesting inconsistent engagement with attentional focus and fluctuating sustained attention. These results are consistent with previously documented characteristics of ADHD, particularly variability of reaction times and an increase in false alarms as shown in Figure.3.

```
Summary Metrics:
          Total Trials  Hits  Misses  Commissions  Hit Rate  Miss Rate  \
Go/No-Go           726   185     541          531  0.254821   0.745179
N-Back             235     0     235          235  0.000000   1.000000

             Mean RT      RT Std
Go/No-Go  1609.460000  544.481634
N-Back     829.192308  415.368466
```

Figure 4: Performance metrics for Go/No-Go and N-Back tasks.

B. N-Back Task (Working Memory Challenge)

Overall accuracy was low in the N-Back condition, especially in increasing difficulty levels, as indicated by participants steadily losing accuracy as the N-value increased. As N-value incremented, participants also displayed moderate to high variability of reaction times, suggesting challenges to maintain engaged and consistent performance due to increased cognitive demand. The overall decline in performance confirmed the N-Back paradigm is sensitive to detecting impairments in selective attention and cognitive flexibility.

C. Combined Behavioral Metrics

When behavioral results were looked at together, they created a multi-dimensional picture of ADHD-related cognitive performance:

- Attention span was manifested by declining accuracy as tasks increased in difficulty.
- Impulsivity was demonstrated by increased commission errors and hazardous premature responses.
- Working memory issues were indicated by poorer performance at the higher N-levels.
- Processing speed issues were identified by varying reaction time for tasks.

Overall, the combined results suggest that the gamified tasks were able to independently and reliably detect ADHD behavioral markers. These findings support the movement toward using real-time logging and dynamically adjusting levels of difficulty in our gamified cognitive screening measures as shown in Figure.4.

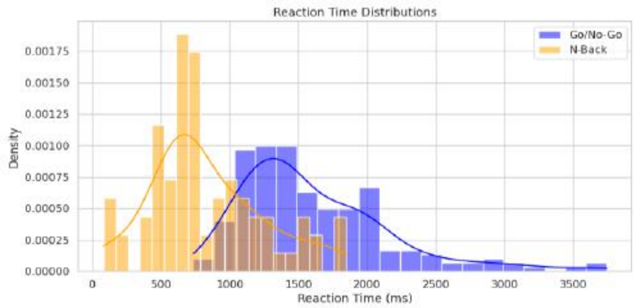

Figure 5: Reaction Time Distributions for Go/No-Go and N-Back Tasks

V. CONCLUSION

This study presented a gamified cognitive assessment framework developed as a means to evaluate behavioral indicators of Attention Deficit Hyperactivity Disorder (ADHD). By implementing the validated Go/No-Go and N-Back paradigms in an interactive game format, the system was able to find objective measures of attention, inhibition and working memory. The use of real-time data logging, adaptive difficulty, and systematic data analysis made for a robust and reliable assessment. The findings indicated that the Go/No-Go task effectively identified sustained attention and inhibition difficulties through hit rates, commission errors, and variability in reaction time, while the N-Back task indicated working memory and cognitive flexibility deficits through declining accuracy and variability as difficulty increased. Collectively, this evidence supports that gamified tasks can elicit ADHD behavioral markers in an experimental setting when they are carefully designed and instrumented. A central benefit of this framework is its scalability and flexibility. Conventional methods for diagnosing ADHD often place a heavy reliance on subjective questionnaires and clinical interviews, which can suffer from recall bias and variability between examiners. The initiation of the proposed ADHD risk assessment framework generates a quantitative, data-driven set of metrics that provide a more strict approach for clinical assessment. The lightweight coding of the framework with Python provides an opportunity to deploy this framework across multiple platforms, such as schools, telehealth, and in low-resource contexts where people cannot access diagnostic facilities. As exciting is the potential to incorporate machine learning models into the analysis pipeline for predicting risk for ADHD through classification. By observing behavioral features, such as reaction times, error rates, and variability, the system can allow for automated risk assessments with optimal accuracy. This will improve the objectivity of the diagnosis, but allows for opportunity of monitoring, early detection, and verified intervention. Next steps on the project will include expanding the sample size, and developing a more diverse sample of participants, as well as additional cognitive tasks to expand language surrounding development in cognitive executive functions. Exploring the next steps may include applying deep learning to increase predictive modeling.

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