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Neuro-Bloom: Machine Learning-based Diagnosis of Learning Disabilities via Gamified Testing

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***Abstract*— This paper proposes a gamified platform that diagnoses children with specific learning disabilities, namely dyslexia, dysgraphia, dyscalculia, and Attention Deficit Hyperactivity Disorder (ADHD). Learning disabilities are neurobiological disorders where cognitive and scholastic skills are affected; these are largely undiagnosed as it requires more awareness, availability of resources, and also relies on traditional subjective screening methods such as behavioral questionnaires and clinical observations [5, 11]. This scenario becomes all the more challenging in schools due to the unavailability of accessible unsupervised diagnostic tools. The Neuro-Bloom platform described here represents an interactive game-based solution which allows self-administered screening of children in the age group of 6–17 years without the help of parental or teacher supervision. Proposed machine learning models such as Random Forest, Support Vector Machine(SVM), Gradient Boosting, and custom Convolutional Neural Network (CNN) ensembles examine response time, accuracy, handwriting, and attention-based game-playing parameters for the detection of learning difficulties. Integrated model accuracies of 94% for dyslexia, 85.7% for ADHD, 82.7% for dysgraphia along with 90% sensitivity in case of dyscalculia, demonstrate the strength of prediction. To the best of our knowledge, this is the first comprehensive game-based unsupervised screening-cum-intervention tool that has been developed for multiple learning disabilities in the Indian educational scenario. NeuroBloom combines engaging gameplays with ML analytics, and as such, is able to offer a scalable, objective, and accessible early detection and personalized intervention solution by responding to some critical lacunae present in conventional diagnostic approaches.**

***Index Terms*— Learning disability, ADHD, Dyslexia, Dysgraphia, Dyscalculia, behavioral patterns, engaging gameplay, specially designed games, Machine Learning, promising accuracy, early detection.**

I. INTRODUCTION

A learning disability is a neurological disorder characterized by differences in brain structure and the way the brain processes information. Kids with learning disabilities have trouble with specific skills despite having average to above-average intelligence. Dyslexia affects approximately 15–20 million school-aged children worldwide, resulting from difficulties with reading, such as slow reading, mispronunciation of words, and poor word recognition. Dysgraphia affects approximately 100 million children, marked by poor overall handwriting, irregular spacing, inability to maintain line margins, and poor punctuation.

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Dyscalculia affects close to 60 million children, who possess difficulties with counting, comparing numbers, and performing the four basic arithmetic operations. ADHD is a neurodevelopmental disorder marked by symptoms of inattention, impulsivity, and hyperactivity that daily life for more than 129 million school-aged children worldwide. Although medication alone cannot cure these conditions, early diagnosis coupled with specialized training can work wonders. Many cases, especially in developing countries like India, go undiagnosed, with children suffering emotional trauma, low self-esteem, and loneliness due to misconceptions that they are perceived as lethargic or lackadaisical. And this unawareness is not confined to rural areas; even urban schools have limited awareness and outdated screening methods, such as long questionnaires on behavior.It also researches developing a gamified platform for detecting dyslexia, dysgraphia, and dyscalculia and ADHD conditions in children aged 6-17 years, which may ultimately enable early identification and provide specific targeted interventions supportive of both academic and emotional growth.

II. LITERATURE SURVEY

Technology-based approaches have shown promising alternatives. Early studies on dyslexia described computer-assisted learning systems that enhanced phonological processing up to 96% accuracy [7–9, 12]. Similarly, dysgraphia detection models reached 90% accuracy in identifying handwriting anomalies [19–21, 24], though most require parental supervision or are limited by language [22, 25]. Dyscalculia research successfully utilized SVM classifiers [33, 36, 38]. Tools like DyscalculiUM and Dyscalc remained confined to older learners and were not engaging for younger users [37]. In ADHD research, SVM and Random Forest models achieved an accuracy of ~75%, while Kinect and VR-based methods achieved F1 scores of 80–85%, but remained bound by expensive hardware and restricted datasets [12, 13].Intervention-based research has focused on gamified learning for improving reading and writing skills [14, 27, 29–30]. Some more platform-specific and age-restricted tools include DysgraphiCoach [26] and MathBoard [42], which showed some potential. Likewise, other Augumented Reality and purely web-based methods showed increased motivation but shared the other two limitations of a lack of language flexibility and accessibility [15, 16, 39–41].

Overall, most of the existing systems are either hardware-dependent, age-restricted, or supervised, thus impeding large-scale deployment in developing regions [5, 10–14]. The proposed Neuro-Bloom platform addresses these challenges through an unsupervised, device-independent, and gamified environment that enables scalable screening and intervention for children aged 6–17 across all four learning disabilities, catering to the diverse linguistic and educational context of India.

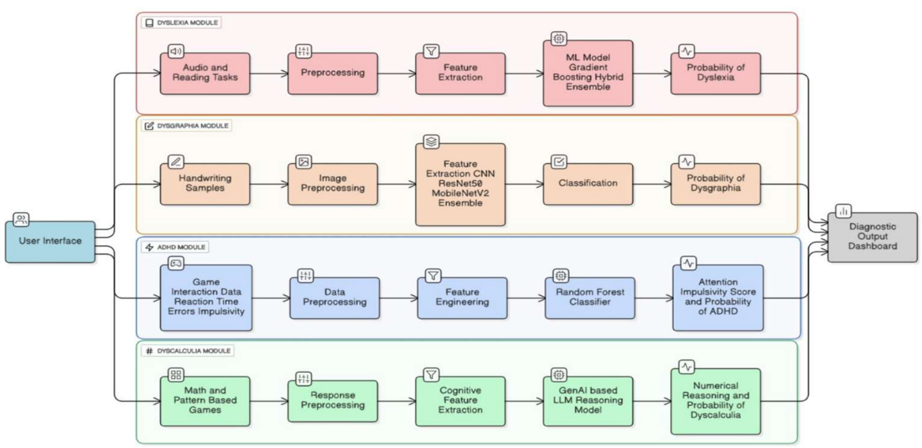


Figure 1. System Diagram

III. METHODOLOGY

The proposed methodology consists of a game-based diagnostic approach. At the core, the methodology is based on making and deploying 4 different games targeted at each of the specific learning disabilities: dyslexia, dysgraphia, dyscalculia, and ADHD. We have designed behavioral and cognitive pattern assessments for respective disorders. Each game targets a particular key area-attention span, reading number sense, and handwriting ability for each child's interaction. The games are designed to be easily accessible without parent or teacher supervision. Furthermore, this system is scaled as follows-In schools, all the children take the diagnostic test provided by us, targeting specific key features, aiming to detect early signs of learning disabilities. Students, based on the results of the test, are shortlisted. One-on-one interaction of shortlisted students happens with clinically verified psychiatrist. Parents are informed the same. Therapy sessions, as per the verdict of the psychiatrist, are taken on our platform.

A. Attention Deficit Hyperactivity Disorder (ADHD)

ADHD is a neurodevelopmental disorder involving persistent symptoms of inattention combined with hyperactivity and impulsivity, affecting 5–7% of school-age children around the world. It is a serious life condition since it adversely impacts the child's skills in performing well academically, socializing with peers, and developing emotionally. Its early identification is paramount because if left untreated, ADHD may result in deleterious long-term repercussions such as low self-esteem, substance abuse, and poor occupational outcomes. Conventional assessment techniques developed from the (Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) criteria, such as Vanderbilt, Conners', Test of Variables of Attention (TOVA), and Continouous Performance Test (CPT), present drawbacks inherent to subjective and time-consuming (30–90 minutes) features because patients need to be supervised by clinical professionals.Machine learning studies also had partial success in the past, with classical models such as SVM and Random Forest achieving an accuracy of ~75%, while deep learning on Kinect Data achieved ~85% F1 score; these were however limited by small datasets with 53 ADHD and 51 neurotypical children alongside expensive hardware requirements. The approach presented here describes a novel framework designed for the game-based multimodal assessment using only standard devices, i.e., keyboard and mouse, so that there is no need for special hardware. Based on DSM-5 and TOVA traits, 1,000 clinically-informed synthetic samples with ages ranging from 6 to 18 years were generated, wherein ADHD cases showed higher reaction time variability as compared to neurotypical controls. Games are designed space-themed to capture behavioral measures representing symptoms of inattention, impulsivity, and hyperactivity, which are analyzed through a Random Forest classifier to achieve superior performance in classification. Future iterations will involve the incorporation of actual pilot data from schools in Pune for the refinement and validation of the model.

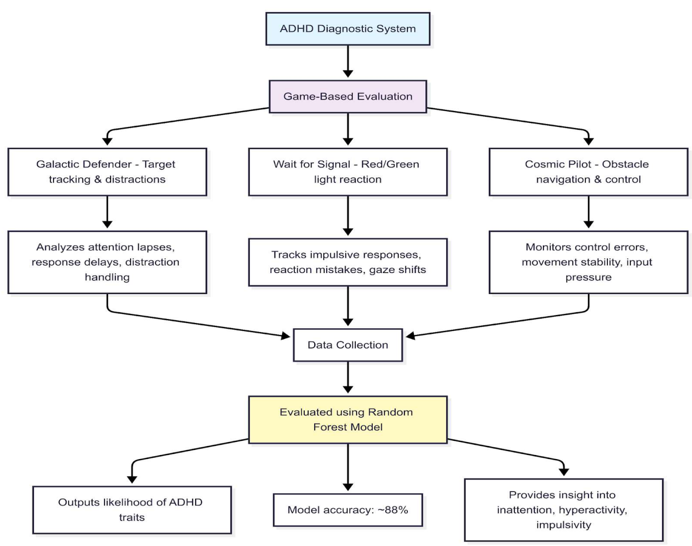


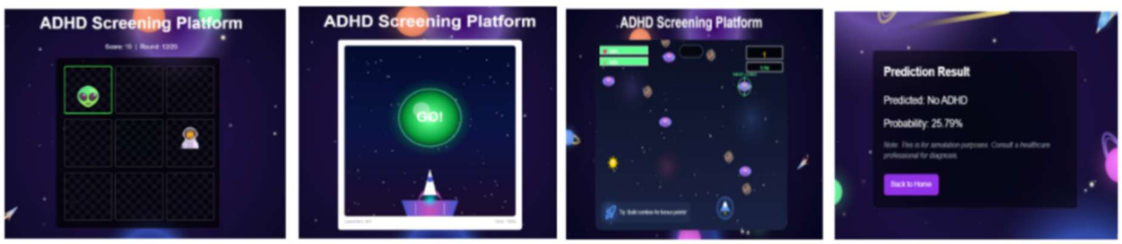
Figure 2. Working flow for ADHD detection

- Game 1: Galactic Defender: This immersive game is strategically deployed to assess the core ADHD symptoms of inattention and impulsivity, calculating these manifestations through the precise measurement of error rate and response time variability.
- Game 2: Wait for Signal: This game was specifically designed to assess two major symptoms of ADHD: impulsivity and distractibility. It does so by calculating these behavioral traits through meticulous analyses of false positives and gaze shifts.

- Game 3: Cosmic Pilot: This game was professionally designed to detect symptoms of attention lapses and motor impulsivity in ADHD by calculating these indicators through the careful measurement of control failures and target precision.

ADHD Dataset and Preprocessing: A synthetic dataset of 1,000 samples was generated using Python (NumPy) based on ADHD literature and TOVA patterns: 500 ADHD, 500 non-ADHD; balanced, 50:50 ratio; ages 6-18. The traits were higher for ADHD cases: Reaction Time variability, Standard Deviation (SD)=250ms versus 150ms for controls; Premature Actions, 20% versus 5%; Movement Errors, 15 versus 4. Overall, features-9 in number-were z-normalized and then split 80/20 for train/validation. This clinically-informed approach ensures realistic distributions for initial validation; future real pilot data from Pune schools is planned.

Training Random Forest Model: The Random Forest classifier was trained using scikit-learn on 80% of the dataset, 800 samples, 100 trees, max depth = 10, min samples split = 5. Feature ranking according to importance was done: Error Rate: 0.22, Reaction Time: 0.18. Hyperparameter tuning using grid search optimized accuracy to 88% on the validation set of 200 samples. This model outperforms the logistic regression baseline of 82% by capturing the non-linear interactions across multi-game metrics.



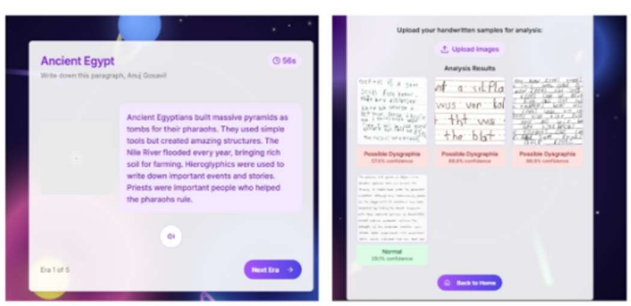
(a) Galactic Defender (b) Wait for Signal (c) Cosmic Pilot (d) Prediction Result

Figure 3. Sample ADHD Interfaces

B. Dysgraphia

Dysgraphia is a learning disability of fine motor skills and written expression that affects approximately 5-20% of school-age children worldwide. Traditional diagnostic methods, mainly the Brave Handwriting Kinder test, present considerable limitations that impede early diagnosis and intervention. The Brave Handwriting Kinder test involves trained professionals manually scoring thirteen handwriting characteristics, taking as long as 15 minutes per child, which offers the potential for subjective bias and inter-rater variability.

Our approach addresses these limitations through a novel multimodal ensemble framework that integrates deep learning architectures with game-based data collection, providing superior diagnostic accuracy without requiring any specialized hardware. In summary, the methodology involves a comprehensive dataset developed in collaboration with licensed therapists and clinical professionals, consisting of around 1,500 handwriting samples collected from children with confirmed diagnoses of dysgraphia. Authentic handwriting specimens were collected from notebooks, homework assignments, and therapeutic assessment materials of children; 1,100 samples came directly from clinical collaborations, while an additional 400 samples were derived from verified online repositories. The collaboration with healthcare professionals helped to ensure the clinical validity and diagnostic authenticity of the training data.



(a)Dysgraphia screening (b) Result

Figure 4. Sample Dysgraphia Interfaces

Our system employs an interactive, game-based interface, built around historical narratives for the natural collection of handwriting samples in an anxiety-free environment for children aged 7-14. The technical architecture is based on the three-model ensemble: a custom CNN (three convolutional layers with Rectifier Linear Unit (ReLU) activation, max-pooling, and dropout regularization), ResNet50 (Residual Network-50) to identify complex spatial relationships, and MobileNetV2 for efficient edge deployment. The ensemble uses soft voting methodology in order to combine the predictions, while the clinically relevant features that align with established diagnostic criteria, such as stroke pressure irregularities, character spacing inconsistencies, and letter formation aberrations, are extracted automatically. This collaborative, clinically-validated approach achieved Overall Accuracy: 82.7% (versus 79.7% best existing method), Precision: 0.83 (against 0.77 state-of-the-art), Recall: 0.81, and F1-Score: 0.82.

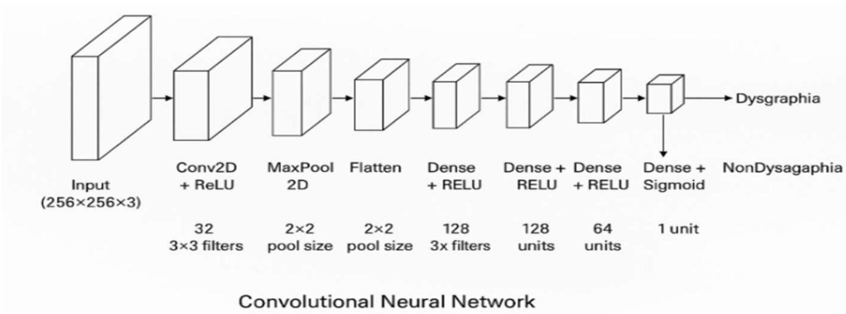


Figure 5. CNN used for Dysgraphia diagnosis based on handwriting images

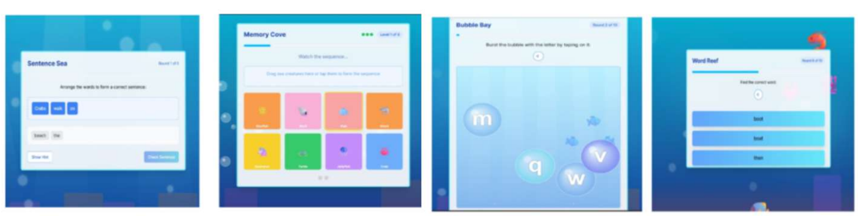
C. Dyslexia

Dyslexia is a learning disorder responsible for hampering the ability of a person to read, write, spell, and decode words despite having the intelligence to do so. A person having this disorder has difficulty in processing phonemes, which makes recognizing and manipulating sounds in words difficult.

After studying recent research papers on Dyslexia, important features were selected to be calculated for the prediction of dyslexia. With those in mind, we created 5 games: Bubble Bay (developing orthographic awareness), Word Reef (lexical decision-making), Memory Cove (working memory capacity), Spell Shore (phoneme-grapheme mapping), and Sentence Sea (syntactic awareness).

Machine Learning Framework: The features derived from the above tasks are used as inputs to the ML models, namely, Random Forest, SVM, Gradient Boosting, and Hybrid Ensembles. It classifies participants as dyslexic or non-dyslexic, thus providing clinicians and educators with supportive diagnostic insights.

Evaluation: The performance of the competing classifiers was compared in various metrics, including: Accuracy, Precision, Recall, F1 Score, and Area under curve(AUC). All performed competitively, with the Gradient Boosting and Hybrid ensembles somewhat better balanced across the different metrics. The best performing model achieved: Accuracy: 94%, Precision: 95% (macro average), Recall: 95% (macro average), F1 Score: 94%.



(c)Dyslexia Sentence Formation (d) Dyslexia Memory Game (a) Dyslexia letter screening (b) Dyslexia word screening

Figure 6. Sample Dyslexia Interfaces

D. Dyscalculia

Dyscalculia is a learning disability that affects a child's ability to understand and manipulate numbers, recognize patterns, and apply basic mathematical concepts. The symptoms commonly involve problems with number sense, sequencing, symbolic representation, spatial reasoning, and time management, in the presence of average or above-average intelligence [12].

- Existing Approaches: Standardized tools, such as the Dyscalculia Screener [13], Number Sense Screener [14], and KeyMath-3 Diagnostic Assessment [15], have been used for several decades in both educational and clinical settings. Although these tools provided validated outcome-based scoring, they mainly assess correctness and do not deeply analyze the processes.
- Proposed Solution: To overcome these deficiencies, we herein present a GenAI-powered screening framework in a gamified "Math Adventure" setting. The online platform uses age-adjusted tasks that reflect cognitive markers associated with dyscalculia (e.g., Dot Counting Game, Number Comparison Game). The LLM includes Time-based parameters, Cultural and age adaptation [18], Knowledge integration [19], and Process-oriented analysis.
- Evaluation Strategy: A pilot study was conducted, involving 30 students aged 6 to 12 years from Vishwakarma Vidyalaya, Pune, India. Our system had a sensitivity of 90.0% in the ability to correctly identify children at risk, compared with traditional screeners at 83.3%. Specificity was 87.5%. The system attained $\kappa = 0.80$ (strong agreement) for inter-rater reliability.

IV. RESULTS

We evaluated our Neuro-Bloom games on labeled data for each disability. For Dyslexia, the best classifier, an ensemble combining Random Forest, SVM, and Gradient Boosting models, achieved an accuracy of 94%, with approximately 95% precision and recall and an F1-score of 0.94 on the test set. For ADHD, using a balanced synthetic dataset of 1,000 samples, the space-themed game series paired with a Random Forest classifier yielded an overall accuracy of 88% and a sensitivity of 85.7%, outperforming the logistic regression baseline of 82%. For Dysgraphia, the handwriting-based ensemble combining a custom CNN, ResNet50, and MobileNetV2 achieved an accuracy of 82.7%. For Dyscalculia, a pilot study involving 30 students demonstrated a sensitivity of 90.0% and a specificity of 87.5% for identifying children at risk.

V. CONCLUSION

The study offers early diagnosis of learning disabilities in children through a fully game-based, interactive screening experience. We came up with entertaining games in relation to dyslexia, ADHD, dyscalculia, and dysgraphia-all these were tailor-made to observe behavioral patterns of each. By converting assessments into entertaining game experiences, we significantly reduce the stress and anxiety often associated with traditional testing, making the process more pleasant and motivating for children. A strong point related to our work is performance, where it outperforms the state-of-the-art approaches in several key dimensions.

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FUTURE SCOPE

In future work, the Neuro-Bloom platform can be extended to capture richer multimodal signals beyond keyboard–mouse gameplay, enabling more fine-grained and ecologically valid screening. For dysgraphia, tablet-based interfaces with stylus input can be integrated to directly record online handwriting dynamics such as stroke trajectory, pressure, and tilt, allowing continuous monitoring of writing difficulties during game-based tasks. Similarly, for ADHD, low-cost inertial sensors and gyroscope-based eye or head-movement tracking can be incorporated to quantify gaze shifts, fidgeting, and micro-movements that reflect real-world inattention and hyperactivity patterns.

Also we are building a platform called Therrato that complements Neuro-Bloom by providing a dedicated therapeutic environment. In Therrato, students identified as potentially having learning disabilities through Neuro-Bloom's screening are referred for follow-up, where licensed therapists work closely with parents. This platform facilitates parent-therapist interaction through guided sessions, feedback reports, and counseling workflows to enable early detection and timely intervention, supporting sustained collaboration beyond the initial screening phase. This approach integrates therapeutic guidance seamlessly with school-based detection for better outcomes.

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