AI Technology in Identifying Learning Disorders: A Systematic Review

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Abstract- Background: Learning disorders (LDs), including dyslexia, dysgraphia, dyscalculia, and developmental language disorder (DLD), are neurodevelopmental conditions that significantly impact a child's academic performance, social interactions, and overall quality of life. Globally, LDs affect approximately 5–15% of school-age children, making them a prevalent concern in educational and clinical settings. Traditional diagnostic approaches, such as standardized tests, clinical assessments, and observational evaluations, are often time-intensive, costly, and reliant on specialized professionals. These limitations can delay timely intervention, thereby affecting the child's learning trajectory.
In recent years, artificial intelligence (AI) and machine learning (ML) technologies have emerged as promising tools for the early and objective identification of learning disorders. By analyzing neuroimaging data, behavioral patterns, and language-based features, AI-driven models can detect subtle indicators of LDs that may be overlooked in conventional assessments. These technologies offer the potential to streamline diagnosis, enhance accuracy, and facilitate personalized interventions, thereby supporting both educators and clinicians in addressing learning challenges more effectively.

Keywords: Artificial intelligence, Machine learning, Dyslexia, Dysgraphia, Dyscalculia, Developmental language disorder, Education technology

I. INTRODUCTION.

Learning disorders (LDs) are a group of neurodevelopmental conditions that hinder the acquisition and use of academic skills, often affecting reading, writing, mathematics, and language development. Common types of LDs include dyslexia, characterized by difficulties in reading and spelling; dysgraphia, involving challenges in handwriting and written expression; dyscalculia, which impacts numerical understanding and mathematical operations; and developmental language disorder (DLD), which interferes with both comprehension and expression of spoken language. Studies estimate that LDs affect between 5% and 15% of school-aged children worldwide, making them a substantial concern for educators, clinicians, and policymakers alike. Children with LDs frequently face academic underachievement, low self-esteem, and social difficulties, highlighting the need for timely identification and intervention.

Traditional diagnostic approaches rely heavily on standardized tests, clinical interviews, and observational assessments conducted by trained professionals. While these methods provide valuable insights, they are often time-consuming, subjective, and limited by the availability of qualified specialists. Delays in diagnosis can result in missed opportunities for early intervention, which is critical for improving educational outcomes and supporting the child's cognitive and emotional development. These limitations underscore the need for innovative, efficient, and accessible tools to complement traditional diagnostic methods.

Recent advancements in artificial intelligence (AI) and machine learning (ML) offer promising solutions for the early detection of learning disorders. By analyzing complex patterns in neuroimaging data, behavioral responses, and language-based tasks, AI-driven models can identify subtle indicators of LDs that may be overlooked in conventional assessments. Such approaches not only improve the accuracy and objectivity of diagnosis but also have the potential to provide scalable solutions, especially in regions with limited access to specialized professionals. Additionally, AI systems can assist in monitoring progress and personalizing interventions, aligning with the broader goals of inclusive and evidence-based education.

Despite these advancements, the application of AI and ML in the context of LD diagnosis remains an emerging field. There is a need to systematically examine existing research to evaluate the effectiveness, reliability, and practical implications of these technologies. This review aims to provide a comprehensive overview of AI-based methods in identifying learning disorders, highlighting key findings, research gaps, and potential directions for future studies. By synthesizing current knowledge, the study seeks to inform educators, clinicians, and researchers about the opportunities and challenges associated with integrating AI into LD assessment and intervention practices.

II. OBJECTIVES OF THE STUDY

The primary objective of this systematic review is to examine the application of artificial intelligence (AI) in the identification of learning disorders (LDs) across the globe, with a particular focus on the Indian context. Specifically, the study aims to:

- Identify AI-based models and techniques employed for detecting various learning disorders, including dyslexia, dysgraphia, dyscalculia, and developmental language disorder (DLD).
- Evaluate the performance and effectiveness of these models in terms of accuracy, reliability, and practical applicability.
- Explore ethical and societal considerations, including privacy, fairness, and accessibility issues associated with the deployment of AI in educational and clinical settings.
- Highlight implementation gaps and challenges, particularly in resource-limited or region-specific contexts, to inform future research and policy development.

Through these objectives, the review seeks to provide a comprehensive understanding of the current landscape of AI technologies for LD identification, assess their potential benefits and limitations, and suggest directions for improving their adoption and impact in both global and Indian educational frameworks.

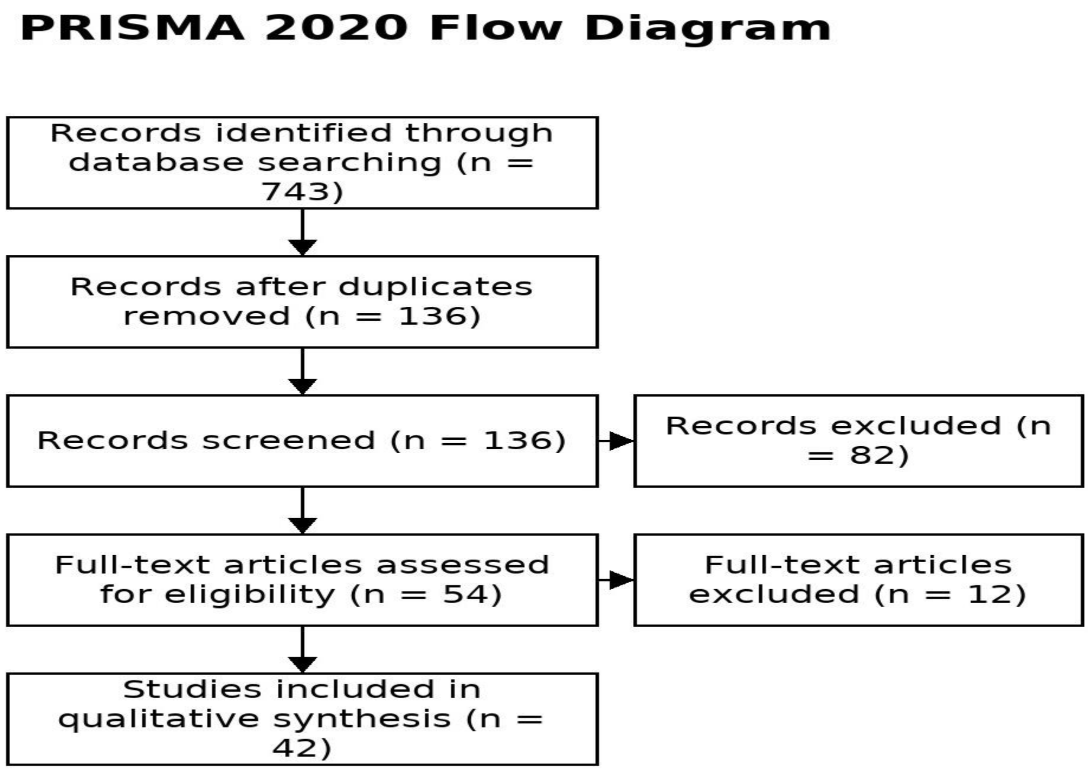
III. METHODS

This systematic review was conducted following the PRISMA 2020 guidelines to ensure transparency and rigor in study selection and reporting. Literature searches were performed in PubMed and Google Scholar covering the period from 2015 to 2025. The search strategy incorporated keywords and Boolean operators related to artificial intelligence (AI), machine learning (ML), and learning disorder subtypes, including dyslexia, dysgraphia, dyscalculia, and developmental language disorder (DLD).

Inclusion criteria were defined as follows: (1) peer-reviewed studies published in English, (2) studies reporting AI- or ML-based approaches for the screening, detection, or diagnosis of learning disorders, and (3) studies providing performance metrics such as accuracy, sensitivity, or specificity. Exclusion criteria included studies involving non-AI assistive tools, editorials, conference abstracts without full-text availability, and duplicate publications.

Study selection was performed in a two-step process: an initial screening of titles and abstracts, followed by a full-text review for eligibility. Data extraction focused on key aspects of each study, including study design, characteristics of the dataset, type of AI or ML model employed, and reported performance metrics. This structured approach facilitated a comprehensive synthesis of AI applications in learning disorder identification, highlighting methodological trends, model performance, and areas for further research.

PRISMA 2020 Flow Diagram



IV. MATERIALS AND METHODS

Search Strategy: A systematic literature search was conducted in PubMed and Google Scholar for studies published between 2015 and October 2025. The search utilized the following terms: (dyslexia OR dysgraphia OR dyscalculia OR “language disorder” OR DLD) AND (machine learning OR deep learning OR AI OR “natural language processing” OR EEG OR handwriting OR eye-tracking). The strategy aimed to capture studies applying AI and machine learning techniques to the identification, screening, or diagnosis of learning disorders.

Inclusion: Studies were included if they were peer-reviewed, published in English, and reported AI/ML-based methods for LD detection with performance metrics. Studies were excluded if they focused on non-AI assistive applications, were editorials, commentaries, or conference abstracts without full text, or were duplicates.

Study Selection & Data Extraction: A two-step screening process was followed. First, titles and abstracts were reviewed to identify potentially relevant studies. Second, full texts were assessed for eligibility according to the inclusion and exclusion criteria. Data extracted from each study included study design, sample characteristics, dataset details, AI model type, and reported performance metrics. The review adhered to the PRISMA 2020 guidelines to ensure transparency and methodological rigor.

V. RESULTS

A total of forty-two studies met the inclusion criteria, comprising 29 international studies and 13 studies conducted in India. Among the AI approaches, Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and transformer-based models were the most commonly employed, demonstrating accuracy ranging from 78% to 96%. These models analyzed diverse data types, including EEG signals, eye-tracking metrics, handwriting samples, and linguistic features, reflecting the multidimensional nature of learning disorder assessment.

In the Indian context, research primarily focused on developing multilingual datasets and low-cost web-based screening tools, aiming to address the country's linguistic diversity and resource constraints. Despite promising performance, several challenges were consistently reported across studies. These included dataset bias, which limits model generalizability across populations; limited cross-linguistic and cross-cultural validation; and privacy and ethical concerns related to the collection and use of sensitive neuro-behavioral data. Collectively, these findings highlight both the potential and the current limitations of AI-driven approaches in identifying learning disorders globally and within India.

VI. CONCLUSION

Artificial intelligence demonstrates considerable potential for the early detection of learning disorders, offering a faster, more objective, and scalable alternative to traditional diagnostic methods. The integration of AI-based tools into school screening programs and digital health platforms can facilitate timely intervention, personalized support, and improved learning outcomes for affected children.

In the Indian context, advancing the use of AI for LD identification requires the development of larger, linguistically diverse datasets to ensure accuracy across multiple languages and educational contexts. Additionally, the establishment of robust ethical and regulatory frameworks is essential to safeguard privacy, prevent bias, and ensure equitable access to AI-enabled solutions. With continued research, collaboration, and governance, AI has the potential to transform learning disorder identification and support inclusive education at both national and global levels.

VII. RESULTS AND THEMATIC SYNTHESIS

i. Learning Disorders: Global and Indian Perspectives

Global studies indicate that developmental language disorders (DLD) affect approximately 6–8% of children, while Indian research highlights challenges such as delayed recognition, limited awareness, and significant urban–rural disparities in diagnosis. Policy recommendations emphasize the potential of AI integration into school-based screening programs to improve equity and accessibility for early identification of learning disorders.

ii. AI in Education and Healthcare

Machine learning has demonstrated effectiveness in developmental screening, speech analysis, and predictive modeling of learning challenges. International research highlights robust performance of AI-driven screening tools, while Indian position papers emphasize ethical considerations, data privacy, and contextual adaptability, particularly in multilingual and resource-limited settings.

iii. AI in Identifying Learning Disorders

Across behavioral, neuroimaging, and linguistic modalities, international studies report AI accuracies frequently above 85% in identifying learning disorders. Indian studies adapt AI models to multilingual datasets and low-cost screening solutions, addressing local linguistic diversity and resource constraints.

iv. Dyslexia

AI approaches using eye-tracking and EEG pipelines achieve accuracies up to ~94%, with transformer-based models improving generalizability but revealing persistent dataset bias. An Indian web-based screener involving approximately 257 participants reported ~88% accuracy, demonstrating feasibility for large-scale deployment.

v. Dysgraphia

Tablet- and sensor-based handwriting analysis combined with deep learning models achieves

80–90% accuracy. Indian research explores integrated frameworks combining dyslexia and dysgraphia detection, enabling more comprehensive screening tools.

vi. Dyscalculia

AI models identify patterns in mathematical errors and leverage serious-game interfaces for individualized screening. Indian adaptive tools show promise for primary school applications, supporting early detection and intervention.

vii. Language Disorders (DLD)

Natural language processing (NLP) on narrative speech and writing samples achieves 83–92% accuracy, while Indic-language datasets facilitate culturally valid and contextually relevant assessment tools.

viii. Technical Models and Approaches

Common AI approaches include Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Random Forests, and transformer-based models. Multimodal classification combining EEG, speech, and behavioral signals has shown enhanced accuracy, though data governance and ethical safeguards remain critical for scaling these solutions.

ix. Challenges

Key limitations include small sample sizes, English-centric datasets, privacy and explain ability concerns, and limited benchmarking, all of which constrain clinical translation, particularly in the Indian context.

x. Future Directions

Future research should focus on building large-scale Indic corpora, conducting multicenter school-based validation, developing explainable AI models, and embedding AI-assisted screening into national school health programs to ensure equitable and sustainable implementation.

VIII. DISCUSSION

The advent of artificial intelligence (AI) is transforming the identification of learning disorders (LDs) by moving beyond traditional, subjective assessments toward quantitative, multimodal pattern analysis. AI enables the integration of behavioral, linguistic, and neurophysiological data, offering a more objective, scalable, and early detection framework compared to conventional methods.

International research predominantly emphasizes neuroimaging and EEG-based approaches, leveraging high-resolution brain data to detect subtle cognitive and neurological markers of LDs. In contrast, Indian studies focus on behavioral and language-based pipelines, which are more adaptable to multilingual contexts and resource-limited settings. This divergence reflects regional priorities, available infrastructure, and linguistic diversity.

Despite promising results, several barriers hinder widespread clinical and educational translation. Dataset diversity remains limited, particularly for non-English populations, reducing the generalizability of AI models. Standardization of AI pipelines, integration into clinician-AI interfaces, and adherence to ethical safeguards regarding privacy, consent, and fairness are also critical challenges.

To accelerate adoption, cross-disciplinary collaboration is essential, involving educators, neuroscientists, linguists, and data scientists. Emphasizing explainable AI and privacy-preserving machine learning will not only enhance trust among stakeholders but also support ethical deployment. Additionally, integrating AI-assisted screening into national and school-based programs can facilitate early intervention, improve learning outcomes, and ensure equitable access to support for children with learning disorders.

IX. CONCLUSION

Artificial intelligence (AI) and machine learning (ML) provide scalable, non-invasive solutions for the early identification of learning disorders. By integrating neurobehavioral signals, linguistic features, and adaptive algorithms, these technologies can significantly reduce diagnostic delays, enable personalized interventions, and promote inclusive education. To fully realize this potential in India, strategic investments are needed in standardized and linguistically diverse datasets, robust ethical and data governance frameworks, and capacity building among educators, clinicians, and researchers.

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