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Recent Advances in Artificial Intelligence for Dyslexia Detection: A Systematic Review

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ABSTRACT

The prevalence of dyslexia, a common neurodevelopmental learning disorder, poses ongoing challenges for early detection and intervention. With the advancement of artificial intelligence (AI) technologies in the fields of healthcare and education, AI has emerged as a promising tool for supporting dyslexia screening and diagnosis. This systematic review aimed to identify recent developments in AI applications for dyslexia detection, focusing on the methods used, types of algorithms, datasets, and their performance outcomes. A comprehensive literature search was conducted in 2025 across databases including ScienceDirect, IEEE Xplore, and PubMed using a combination of relevant MeSH terms. The article selection process followed the PRISMA guidelines, resulting in the inclusion of 31 eligible studies. Data were extracted on AI approaches, algorithm types, dataset characteristics, and key performance metrics. The results revealed that machine learning (ML) was the most widely applied method (58.06%), followed by multi-method (22.58%), deep learning (16.13%), and large language models (3.23%). Among the ML algorithms, Random Forest and Decision Tree were the most commonly used due to their robustness and performance on structured datasets. In the deep learning category, CNN were the most frequently used models, especially for image-based and sequential input data. The datasets varied widely, including digital cognitive tasks, EEG, MRI, handwriting, and eye-tracking data, with several studies employing multimodal combinations. Ensemble and hybrid models demonstrated superior performance, with some achieving accuracy rates exceeding 98%. This review highlights that AI, particularly ML and multimodal ensemble methods, holds strong potential for improving the accuracy, scalability, and accessibility of dyslexia detection. Future research should prioritize large-scale, multimodal datasets, interpretable models, and adaptive learning systems to enhance real-world implementation.

1. Introduction

Dyslexia is one of the most common specific learning disorders, characterised by difficulties in accuracy and/or fluency in reading words, as well as difficulties in spelling and automatic word recognition [1]-[4]. The disorder is not caused by intellectual retardation, sensory impairment or inadequate learning opportunities, but is rooted in differences in language processing in the brain [5]-[7]. It is estimated that dyslexia affects 5-15% of the school-aged child population worldwide [8]-[10], and can have long-term consequences in educational, social and psychological aspects if not detected and treated early [11], [12]. Early detection of dyslexia is crucial to enable timely and effective interventions, but the biggest challenges today are limited professional resources, delays in the diagnosis process, and the large variability in clinical manifestations of dyslexia between individuals [13]-[15]. Conventional methods of diagnosing dyslexia generally rely on psychometric assessments by experts, which are time-consuming, expensive, and difficult to reach widely [16], [17]. Therefore, there is an urgent need to develop an efficient, scalable and accurate detection system with the support of modern technology.

AI has emerged as a promising multidisciplinary approach in detecting various neurocognitive disorders, including dyslexia [18]-[21]. AI is defined as "the science and engineering concerned with the computational modelling of intelligent behaviour and the development of systems capable of exhibiting such behaviour" [22], [23]. In the context of dyslexia, AI has the potential to identify complex cognitive and linguistic patterns from data such as handwriting, voice recordings, reading texts, to brain activity, which were previously difficult to capture with traditional techniques [24]-[26]. With the increasing volume of digital data from students and patients, and the proliferation of sensors and data collection systems, AI-based analyses are becoming highly relevant and necessary to accelerate dyslexia screening and diagnosis [27], [28]. Furthermore, advancements in XAI allow researchers and clinicians to better interpret the decision-making process of these models, fostering greater trust and clinical applicability. In addition, integrating AI into educational platforms and healthcare systems opens opportunities for real-time monitoring and personalized interventions tailored to individual learning needs.

Various AI approaches have been used in dyslexia detection studies, especially machine learning (ML) and deep learning (DL) techniques, which have been shown to be able to classify individuals with dyslexia based on linguistic, visual or phonological traits [29]-[31]. These methods include algorithms such as SVM, ANN, Random Forest, CNN, and NLP, which are used to process handwritten data, reading text, and EEG signals [32]-[35]. Some models also incorporate multimodality data, such as the integration of brain activity and reading performance, to improve classification accuracy [36]. In addition to EEG, neuroimaging modalities such as MRI and fMRI are increasingly utilized to capture structural and functional brain differences associated with dyslexia [37]. Eye-tracking technology has also been applied to analyze visual fixation patterns and reading behaviors, providing complementary insights into cognitive processing deficits [38]. Recent research trends emphasize combining these diverse data sources into unified AI frameworks, which not only enhance detection accuracy but also contribute to a deeper understanding of the neurocognitive basis of dyslexia [39].

As scientific publications in this field increase, it is important to conduct a systematic review to map the current AI approaches that have been used in dyslexia detection, evaluate their effectiveness and limitations, and identify future research directions. Therefore, this study aims to systematically review recent advances in AI applications for dyslexia detection, with a focus on methodology, types of data used, algorithm performance, and potential applications in clinical and educational settings.

2. Methods

2.1. Research Question

This study aimed to identify various applications of AI in dyslexia detection. We reviewed articles reporting AI methods and techniques used to detect or diagnose dyslexia in various populations. The study population consisted of individuals suspected or diagnosed with dyslexia, including children, adolescents and adults. The interventions reviewed were the use of AI techniques, both machine learning and deep learning, to detect dyslexia based on linguistic, visual, handwriting, voice or neurophysiological signals such as EEG. This study did not directly compare AI with conventional methods, so it did not include comparison as a design element. The outcome of this review is the identification of recent trends, the types of data used, the most commonly applied algorithms, and the performance and limitations of AI techniques in the context of dyslexia detection.

2.2. Search Strategy

This study is a systematic review conducted in 2025. Literature searches were conducted on major scientific databases, including ScienceDirect, IEEE Xplore, and PubMed, using relevant keyword combinations based on Medical Subject Headings (MeSH) terms and related synonyms (Table 1). The entire article search and selection process followed the PRISMA guidelines. The search was conducted independently by two researchers to minimise potential bias in study selection. In case of discrepancies or contradictions in article selection, the final decision was agreed upon through discussion with an independent third reviewer. Search criteria were limited to articles written in English and published within the last five years (2020-2024) to ensure a focus on recent developments in the application of artificial intelligence for dyslexia detection.

2.3. Inclusion and Exclusion Criteria

Inclusion criteria were original research articles, experimental studies, and meta-analysis reports that addressed the application of AI for dyslexia detection. In addition, only works that presented model performance evaluations, such as accuracy, sensitivity, specificity, precision, F1-score, or AUC, were included. Studies should utilise AI-based methods, including machine learning, deep learning, or other data-driven techniques used for dyslexia classification or prediction. Exclusion criteria were articles not written in English, articles without full-text access, as well as publication types other than original studies or meta-analyses. Review articles, commentaries, opinion pieces, letters to the editor, short communications and conference articles were excluded from this review. Studies that were not conducted on human subjects were also excluded. In addition, papers that did not include quantitative measurements of AI model performance were also eliminated.

2.4. Selection Process

The article selection process in this review followed the PRISMA guidelines as shown in Fig. 1. After screening titles, abstracts and full-text reviews, 31 articles were finally selected for further analysis. All stages of selection and evaluation of article quality were conducted independently by two researchers to ensure objectivity and avoid selection bias. If there was a difference of opinion between the two researchers, the final decision was determined through discussion with an independent third reviewer.

For analysis purposes, data from each article was extracted using a standardised form that included seven main categories: (1) author name, (2) year of publication, (3) artificial intelligence (AI) method applied, (4) type of algorithm used, (5) type of data used to detect dyslexia, including reading text, handwriting, audio-visual, and neurophysiological signals such as EEG, (6) characteristics of the study population or sample, and (7) best performance of the model based on evaluation metrics such as accuracy, sensitivity, specificity, F1-score, and AUC. All extracted data were analysed, summarised, and presented in tables and graphical illustrations in accordance with the objectives of this systematic review.

3. Results

According to the study search terms, 31 papers were reviewed in detail. Table 2 shows a categorical breakdown of the articles by year of publication, with most of the papers (n=10) published in 2024, signalling the increasing trend of current research in the field of applying AI for dyslexia detection. In this review, we analysed the various AI methods used in these studies.

Fig. 2 and Table 3 present the frequency distribution of the use of AI methods in dyslexia detection. The results show that Machine Learning (ML) methods were the most dominant, used in 18 out of 31 studies (58.06%). This was followed by Multi Methods (MM) in 7 studies (22.58%), which combined two or more AI techniques such as ML, DL, ensemble, or fuzzy techniques.

Furthermore, Deep Learning (DL) was used in 5 studies (16.13%), while Large Language Model (LLM) was only used in 1 study (3.23%). These findings suggest that the conventional ML approach is still the top choice in dyslexia detection studies, most likely due to its flexibility in handling different types of datasets, as well as its stability in classification performance. Meanwhile, multi-method approaches are gaining ground and offer competitive results, especially when used on multimodal datasets such as a combination of EEG and MRI data, or visual and linguistic data.

Table 1. Search strategy of the research

Search strategy	
Database	ScienceDirect, IEEE Xplore, and PubMed (2020-2024)
Limits	Inclusion criteria included English-language sources and studies in human populations.
Data	January 1, 2020 to December 31, 2024
Search Query	("Dyslexia" OR "Dyslexic") AND ("Detection" OR "Classification" OR "Prediction" OR "Prognostic") AND ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning")

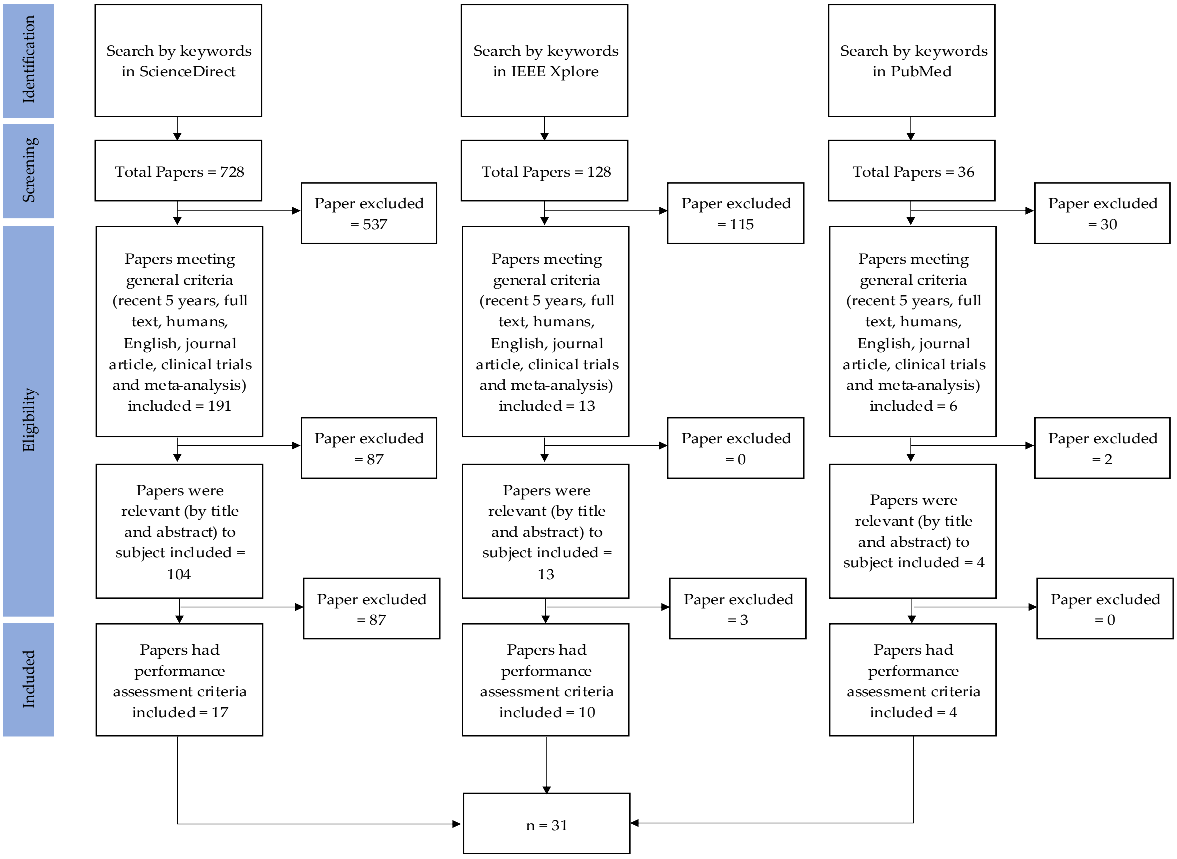

Fig. 1. PRISMA process for data collection

Table 2. Selected papers according to the specified criteria

Authors & Year	AI methods	Algorithm used	Dataset	Characteristics of dataset	The best algorithm	Performance
Zahia et al., 2020 [40]	Deep Learning	3D CNN	fMRI scans of 55 children (19 dyslexic, 19 control, 17 monocular vision)	3 reading tasks; 165 3D brain activation volumes (3 per child); preprocessed with SPM12	3D CNN	Accuracy = 72.73%, Sensitivity = 75%, Specificity = 71.43%, Precision = 60%, F1-score = 67%

Authors & Year	AI methods	Algorithm used	Dataset	Characteristics of dataset	The best algorithm	Performance
Sobnath et al., 2020 [41]	Machine Learning	Decision Tree, Logistic Regression, LDA, GaussianNB	270,934 UK disabled student records (DLHE survey 2012–2017)	Categorical data on age, disability type, HE institution, degree class, qualification level, SOC jobs	Decision Tree, Logistic Regression	Accuracy = 96%
Rello et al., 2020 [42]	Machine Learning	Random Forest	3,644 Spanish-speaking participants (ages 7–17), include 392 with diagnosed dyslexia	196 features from gamified online linguistic tasks, including clicks, accuracy, and memory tasks	Random Forest with weighted attributes	Accuracy = 80.8%, Recall = 80.9%, Precision = 80.7%, ROC = 0.868 (for 7–11 age group)
Nerušil et al., 2021 [43]	Deep Learning	Convolutional Neural Network (CNN)	Eye-tracking data from 185 children (97 high-risk, 88 low-risk)	Gaze x-axis signals during text reading; preprocessed using zero-padding or interpolation + spectrum	3-layer CNN	Accuracy = 96.6%, TPR = 97.8%, TNR = 95.4%
Usman et al., 2021 [44]	Deep Learning	Inception-V3, Cascaded CNN, ResNet50	MRI from OpenNeuro (n=97, children 8.7–15.5 years old), and BNU C-BIRD (n=25, adults 19–30 years old)	Multi-site MRI, T1-/T2-weighted & fMRI, varying protocols; 390,400 patches for training	ResNet50 (with Gaussian smoothing + Modified Histogram Normalization)	Accuracy = 94.7%, Sensitivity = 95.8%, Specificity = 94.9%, F1-Score = 95.4%
Bosco et al., 2021 [45]	Deep Learning	DeepEva model (2-layer LSTM)	Italian corpus (harvested + PACCSS), English corpus (Newsela)	Italian corpus = 100,000 sentences labeled by complexity (CEFR levels); English corpus = 530,000 sentences labeled by document complexity levels	DeepEva model (2-layer LSTM)	Italian Corpus (Recall = 87.2%, Precision = 86.2%, F1-score = 86.2%) and English Corpus (Recall = 87%, Precision = 89%, F1-score = 88%)
Paola et al., 2021 [46]	Machine Learning	J48 Decision Tree	Sample of children	Children's interaction data with literacy exercises based on Orton-Gillingham method	J48 Decision Tree	Accuracy = 98.81%, Precision = 100%, Recall = 97.62%, F1-measure = 98.80%
Raatikainen et al., 2021 [47]	Machine Learning	SVM and Random Forest	Eye-tracking data from 161 students (30 dyslexic)	Eye movement features during internet reading tasks, gaze fixations and saccades measurements	SVM with feature selection by Random Forest	Accuracy = 89.7%, Recall = 84.8% (balanced SVM with RF-selected features)
Singer et al., 2022 [48]	Machine Learning	Ordinal CART, Ordinal Random Forest, Ordinal AdaBoost	2300 exam records from 1313 Israeli engineering students (343 with LIs)	17 features : student profile, diagnosis, course/exam info, exam behavior, grade (5-level ordinal scale)	Ordinal CART	Accuracy = 0.356, AUC = 0.594, MSE = 2.538
Molina et al., 2022 [49]	Machine Learning	SVM	EEG data from 48 children (skilled & dyslexic)	Auditory stimuli EEG, 32 channels	SVM with graph features from PAC networks	Accuracy = 72.9%, Sensitivity = 72.3%, Specificity = 74.7%, AUC = 73.3%
Zeema et al., 2022 [50]	Machine Learning	Neutrosophic C-means Clustering optimized by	Dyslexia dataset from KEEL repository, 65	Low-quality dataset with incomplete, vague, ambiguous,	ONCMC-ABF (Optimized Neutrosophic	Precision = 96.9%, Recall = 98.7%, F-measure = 97.8%

Authors & Year	**AI methods**	**Algorithm used**	**Dataset**	**Characteristics of dataset**	**The best algorithm**	**Performance**
		Artificial Bacterial Foraging Algorithm (ONCMC-ABF)	instances with 12 attributes	and noisy information	C-means Clustering with Bacterial Foraging)	
Kaisar et al., 2022 [51]	Machine Learning	SVM, Logistic Regression, Decision Tree, AdaBoost, Gradient Boosting (GB), Extreme Gradient Boosting (XGB)	Online gamified test data, 3,644 participants with 196 features (demographic + test responses)	Imbalanced data (89.2% non-dyslexic, 10.7% dyslexic participants)	XGB with ADASYN	Accuracy = 89.8%, Recall = 83.5%, ROC = 89.9%
Deveau et al., 2022 [52]	Machine Learning	Random Forest	Gameplay metadata from GuessWhat? game, 28 children with ASD, 21 neurotypical controls	Behavioral data during game play with emotion recognition prompts, structured video metadata	Random Forest	AU-ROC = 74.5%, Recall = 76.9%
Carioti et al., 2023 [53]	Machine Learning	Classification and Regression Tree (CART)	ReadFree dataset: 210 children (Italian monolingual and minority-language)	Children aged 8–13 years; 3 groups (monolingual good readers, poor readers, MLC); assessed on 12 tasks using auditory/ visual stimuli	CART	Accuracy = 86% (monolinguals), Accuracy = 76% (MLC)
Parmar et al., 2023 [54]	Machine Learning	SVM with nonlinear kernels (RBF, Polynomial, MLP)	EEG Dataset 1 (391 children, 8–12 years) and EEG Dataset 2 (52 children, 7–12 years)	Multi-channel EEG, different cognitive tasks (N-Back, Spatial N-Back, P300 Oddball)	SVM with RBF kernel using Wavelet Scattering Transform features	Dataset 1 (accuracy = 98.72%) and Dataset 2 (accuracy = 98.67%)
Joshi et al., 2023 [55]	Deep Learning	Autoencoder (AE) + 3D Convolutional Neural Network (CNN)	MRI brain images from 192 children (96 reading disability, 96 controls)	Multi-site data, 3D Jacobian determinant images representing brain volume differences	Combined AE + CNN model	Accuracy = 77%, Precision = 75%, Recall = 78%
Kunhoth et al., 2023 [56]	Machine Learning	AdaBoost, Random Forest, SVM, KNN	Handwritten data from 120 children (57 dysgraphia, 63 normal), Slovak orthography	Online handwriting features including On-Surface and In-Air activities; 175 features extracted (kinematic, dynamic, temporal, spatial)	AdaBoost with combined On-Surface + In-Air features	Accuracy = 80.8%, Precision = 83.3%, Recall = 78.5%, F1-score = 80.1%
Orsoni et al., 2023 [57]	Machine Learning	Self-Organizing Maps, K-means, AdaBoost, Artificial Neural Networ	292 Italian secondary school students (aged 11–15), subset of 105 clinically assessed students	Cognitive tests including logical reasoning, visual perception, visuospatial attention, working memory; imbalanced classes handled by SMOTE	Artificial Neural Network (ANN)	ANN global testing accuracy = 91.5%, balanced accuracy = 91.7%, weighted F1-score: 92%

Authors & Year	AI methods	Algorithm used	Dataset	Characteristics of dataset	The best algorithm	Performance
Meena et al., 2023 [58]	Multi Methods	LDA, BLDA, SLDA, KNN, MLP, ELM, Tree Bagger	32 children (16 dyslexic, 16 control), Hindi language typing tasks with eye-tracking	Typing speed on 10 Hindi words, measured across 3 input modalities (TS, ET, ETSS), with visual & auditory feedback	Linear Discriminant Analysis (LDA)	AUC = 91%
Vajs et al., 2023 [59]	Multi Methods	Convolutional Autoencoder (CNN AE) + ML classifiers (LR, SVM, KNN, RF, AdaBoost)	Dataset 1 (30 Serbian children (15 dyslexic)) and Dataset 2 (185 Swedish children (97 dyslexic))	Eye-tracking data during reading; plotted as grayscale images of gaze paths; cross-language, cross-protocol	Logistic Regression (on CNN AE features)	Dataset 1 (accuracy = 85.6%) and Dataset 2 (accuracy = 82.9%)
Seshadri et al., 2023 [60]	Machine Learning	KNN and SVM	EEG data from 30 children (15 dyslexic, 15 non-dyslexic) during sustained attention task	19-channel EEG, graph features (Clustering Coefficient, Path Length, Efficiency, Small-Worldness)	KNN (k = 3)	Accuracy = 96.7%, AUC = 96%, Sensitivity = 93%, Specificity = 100% (5-fold cross-validation)
Shravya et al., 2024 [61]	Multi Methods	LSTM, RNN, CNN, KNN, SVM, ResNet, DenseNet, MobileNet, VGG16	MNIST, A-Z Kaggle, Quick Draw! Doodle	Handwritten digits, alphabets, doodles	LSTM (digits), RNN (characters), CNN (doodles)	Accuracy = 98.57% (digits recognition), Accuracy = 98.80% (character recognition), Accuracy = 97.09% (doodle recognition)
Zaibi et al., 2024 [62]	Machine Learning	Gradient Boosting, Random Forest, AdaBoost, SVM, Decision Tree	Handyg23 dataset (handwriting samples from neurodegenerative and healthy controls)	120 children aged 7–12 years, 12 different handwriting/drawing tasks, spatial, temporal, kinematic features extracted using Beta-elliptic segmentation theory	Gradient Boosting and Random Forest	Gradient Boosting (Accuracy = 99%), Random Forest (Accuracy = 99%)
Barnes et al., 2024 [63]	Machine Learning	Gaussian Mixture Model (GMM) for feature quantization + XGBoost classifier	EEG data from 48 children (15 dyslexic, 33 controls) from LEEDUCA research platform, ages 4–8	32-channel EEG with auditory stimuli at 4.8, 16, 40 Hz; cognitive and linguistic assessments	XGBoost classifier on GMM-quantized features	AUC = 82.1%, Balanced Accuracy = 79.09%
Sbiaa et al., 2024 [64]	Machine Learning	Random Forest, AdaBoost, CatBoost, Artificial Neural Network (MLP)	Cognitive features dataset from young learners curated via 21 questionnaires validated by pedopsychiatrist	Behavioral and cognitive data from children capturing reading, writing, attention, problem-solving	Multi-Layer Perceptron (MLP)	Accuracy = 92.1%, F1-Score = 92.2%
Remadi et al., 2024 [65]	Large Language Model	Large Language Model (GPT-3.5-Turbo)	Vrailexia project (survey (n=2106), VR (n=100), interviews)	Multilingual, structured & unstructured, dyslexia-focused	Large Language Model (GPT-3.5-Turbo)	Precision = 67.96, Recall = 63.06, F1-score = 65.42
Vaitheeshwari et al., 2024 [66]	Multi Methods	Random Forest, SVM, DNN, XGBoost,	VR-based eye movement data from 14 participants (10	Eye-tracking data (fixation, saccades, saliency maps), reading tasks in Chinese script, text	Fusion model (CNN + BERT + DNN with voting mechanism)	Accuracy = 98%, F1-score = 99%, Recall = 100%, Precision = 99%

Authors & Year	AI methods	Algorithm used	Dataset	Characteristics of dataset	The best algorithm	Performance
		BERT, CNN, Voting Fusion	dyslexic, 4 control)	complexity, visual & semantic features		
Gasmi et al., 2024 [67]	Machine Learning	SVM, KNN, Decision Tree, Logistic Regression, Naive Bayes, Random Forest, XGBoost	Dyslexia dataset (n=3,644; ages 7–17; 392 dyslexic cases)	196 features (4 demographic + 192 from 32 interactive test questions), highly imbalanced classes	Ensemble Voting Model (Random Forest + Naive Bayes with GA-based weight selection)	Accuracy = 90.4%, F1-score = 94.8%
Sellamuthu et al., 2024 [68]	Multi Methods	MobileNetV2, ResNet50, InceptionV3, Novel CNN, Multimodal Concatenation Model	2,536 clinical samples (facial images + ADOS scores (autistic & non-autistic children))	Real-world images, ADOS behavioral scores (Social Affect, Repetitive Behaviors, Severity Score)	Multimodal Concatenation Model	Accuracy = 97.05%
Alkhurayyif et al., 2024 [69]	Multi Methods	SWIN Transformer, CFC Network, CatBoost, XGBoost, Extra Trees	MRI (Dataset 1: n=58, Dataset 2: n=264), EEG (n=130), publicly available	MRI (2D slices from 3D brain volumes), EEG (128-channel sensor data, Delta–Beta bands)	Multimodal Ensemble Model (SWIN + CFC + CatBoost + XGBoost + Extra Trees)	Accuracy = 98.5% (MRI) and Accuracy = 98.7% (EEG)
Xiong et al., 2024 [70]	Multi Methods	CNN (dual), LSTM, Reinforcement Learning	RECOLA dataset (audio + facial images); 46 participants; test: 9 samples, training: 27 samples	Audio-visual data with emotional labels (Arousal & Valence)	Hybrid CNN + LSTM	Arousal (RMSE = 0.1905, MAE = 0.1570, CCC = 0.6146, R = 06309), Valence (RMSE = 0.1658, MAE = 0.1356, CCC = 0.6751, R = 06975)

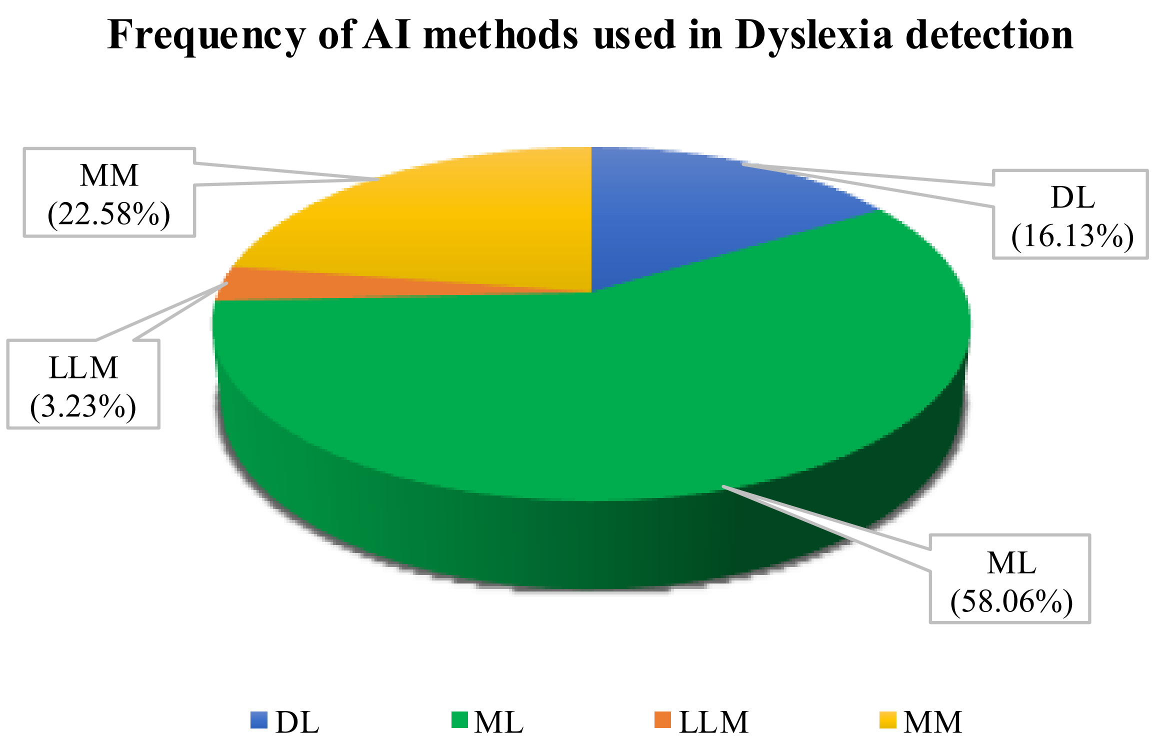

Fig. 2. Frequency of AI methods used in Dyslexia detection, with DL: Deep Learning, ML: Machine Learning, LLM: Large Language Model, and MM: Multi Methods

Table 3. Frequency of AI methods used in Dyslexia detection (%)

AI methods in Dyslexia Detection	Frequency
Machine Learning (ML)	18 (58.06%)
Deep Learning (DL)	5 (16.13%)
Multi Methods (MM)	7 (22.58%)
Large Language Model (LLM)	1 (3.23%)
Total	**31 (100%)**

In this review, the algorithms used for dyslexia detection show a diversity of approaches from both machine learning (ML) and deep learning (DL) domains. In addition, one study may utilise more than one type of AI algorithm. As shown in Fig. 3, the most frequently used algorithm was Convolutional Neural Network (CNN), appearing in 7 studies. CNNs are especially favoured in studies using visual data such as MRI images, handwriting, or visual maps from eye-tracking data, due to their ability to automatically extract spatial and structural features. Random Forest (RF) and Decision Tree (DT) also stood out, being used in 5 and 4 studies respectively. Both algorithms are widely used in structured datasets based on quizzes or text-based cognitive outcomes. Support Vector Machine (SVM), Long-Short Term Memory (LSTM), and Extreme Gradient Boosting (XGB) were used in an equal frequency of 3 studies, suggesting that both sequential learning (LSTM) and boosting (XGB) based models also promise competitive performance in certain cases. Meanwhile, Logistic Regression (LR) was used in 2 studies. The 'Other' category includes 15 studies, showing that many studies used mixed or specialised models such as Large Language model, Autoencoder, CatBoost, Ensemble Voting, Gaussian Mixture Models, to Fuzzy Logic and Transformer-based models.

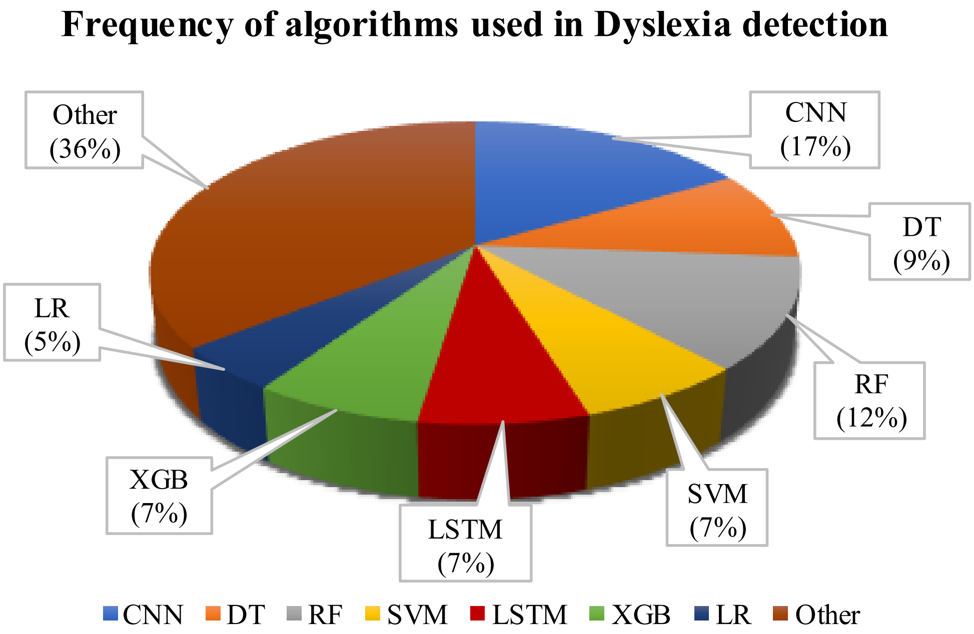

Fig. 3. Frequency of algorithms used in Dyslexia detection, CNN: Convolutional Neural Network, DT: Decision Tree, RF: Random Forest, SVM: Support Vector Machine, LSTM: Long-Short Term Memory, XGB: Extreme Gradient Boosting, and LR: Logistic Regression

In terms of data, an analysis of the types of datasets used (Fig. 4) shows that the most common source of data came from cognitive tests, used in 12 out of 31 studies (one study may use more than one type of dataset). These cognitive tests were typically based on digital linguistic tasks, online quizzes or gamified activities designed to measure phonological awareness, working memory, and visual and syntactic abilities. This demonstrates the dominance of language function and cognition test-based approaches as the foundation of AI-based dyslexia detection. Furthermore, EEG emerged as the most widely used physiological dataset (5 studies), followed by handwriting, eye-tracking, and MRI, each in 4 studies. EEG and MRI data were used to measure brain activity and neuroanatomical structures, while handwriting and eye-tracking data were used to evaluate fine motor functions and visual attention patterns during reading. Audio-visual datasets, although relatively new, were used in 3 studies and showed potential to support multimodal diagnosis, especially in studies based on emotion recognition or naturalistic interaction.

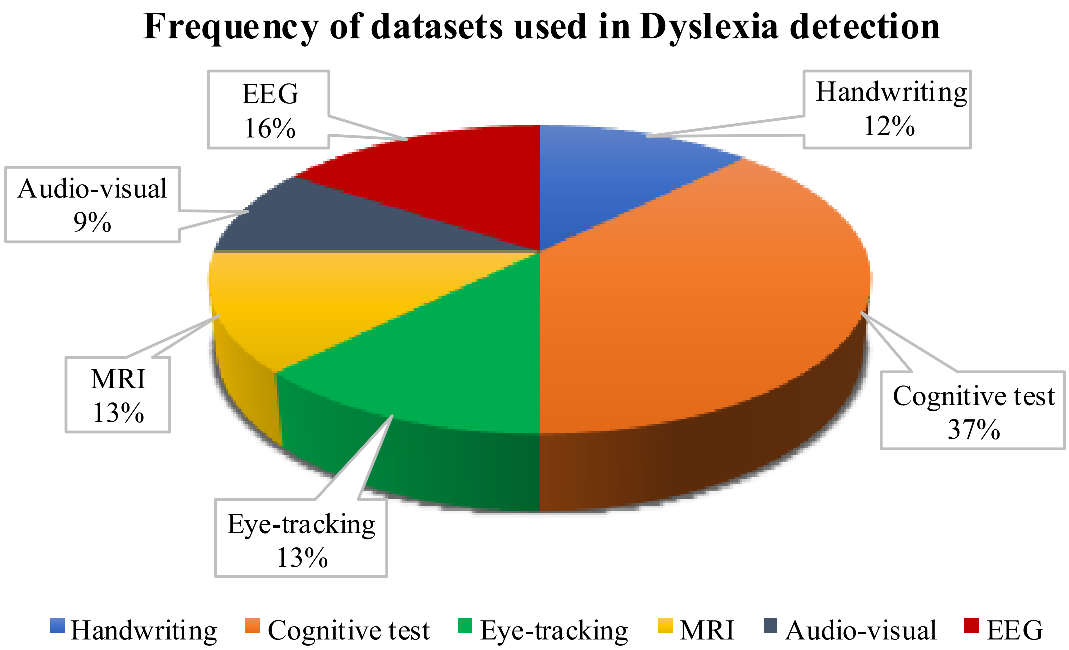

Fig. 4. Frequency of datasets used in Dyslexia detection

These results suggest that non-invasive data-driven and digital interaction-based approaches are still the mainstream in the development of AI-based dyslexia detection systems. However, future trends point to the increasing use of multimodal data that combines physiological signals (such as EEG) [71], behavioural data (such as cognitive tests) [72], and visual signals (such as eye-tracking and handwriting) to improve model accuracy and generalization [73]. Integrating these diverse modalities not only enhances the robustness of detection systems but also provides a more comprehensive understanding of the neurocognitive mechanisms underlying dyslexia. Moreover, such multimodal frameworks pave the way for the creation of personalized diagnostic tools, enabling early interventions that are better tailored to individual profiles and learning needs.

4. Discussions

This study revealed that the most popular artificial intelligence methods used in dyslexia detection are Machine Learning (ML), Deep Learning (DL), Multi-Methods, and Large Language Model (LLM). Of all the studies reviewed, Machine Learning was predominantly used, accounting for more than half of the total articles. The popularity of ML is most likely due to its ability to handle heterogeneous and tabular datasets with good computational efficiency. Among the ML algorithms used, Random Forest and SVM are most commonly chosen. RF algorithms are widely used due to their ability to reduce the risk of overfitting through an ensemble of decision trees. This is seen in studies using interactive and cognitive datasets such as in Rello et al. (2020) who reported an accuracy of up to 80.8% [42]. Meanwhile, SVMs with nonlinear kernels (RBF, Polynomial, MLP) showed high performance in EEG signal analysis in the study of Parmar et al. (2023), with accuracy close to 99% [54].

Deep Learning has also begun to develop rapidly, especially in the analysis of complex image and signal data such as MRI, EEG, and eye-tracking-based visual data. Convolutional Neural Networks (CNN) algorithms dominate this DL approach, as in the study by Nerušil et al. (2021) who recorded 96.6% accuracy on eye-tracking data [43], and Usman et al. (2021) with 94.7% accuracy on MRI [44]. CNNs have the advantage of automatic feature extraction from spatial data, making them an ideal choice in neuroimaging-based approaches. Multi-method models, which combine various AI techniques such as ensemble learning, transfer learning, and multimodal approaches, have gained popularity in recent years. This is fuelled by the complexity and variety of datasets in dyslexia studies. For example, Alkhurayyif et al. (2024) applied SWIN Transformer and CatBoost to a combination of EEG and MRI with a very high accuracy rate (98.7%), demonstrating the advantages of hybrid approaches in improving model accuracy and generalisation [69].

Large Language Models (LLM), such as GPT-3.5 Turbo used by Remadi et al. (2024), are still relatively rarely applied in dyslexia detection [65]. Despite showing promising results in processing multilingual and heterogeneous data, the overall performance is still limited compared to other methods, with a precision of about 67.96% and F1-score of 65.42%. Nevertheless, the future potential of LLM is still great, especially in clinical scenarios based on text interaction and linguistic data. In addition, Table 2 (containing selected papers) shows that the best algorithms tend to come from ensemble and multimodal approaches, which utilise more than one AI technique at a time. For example, the ensemble Voting Model in Gasmi et al. (2024) achieved an accuracy of 90.4% with an F1-score of 94.8% [67]. The combination of several algorithms such as Random Forest and Naive Bayes optimised using Genetic Algorithm proved effective in handling imbalanced datasets.

CNN algorithms have also consistently shown superior performance in processing visual and neuroimaging data. For example, Nerušil et al. (2021) used CNN for eye-tracking data with a True Positive Rate of up to 97.8% [43]. This indicates that CNNs are able to efficiently extract visual features typical of dyslexic individuals. On the other hand, classic ML algorithms such as Random Forest and SVM still show high relevance especially on quiz-based datasets or tabular features. Studies by Rello et al. (2020) [39] and Raatikainen et al. (2021) [47] show that RF and SVM with proper feature selection can achieve high accuracy, as well as have advantages in interpretability compared to DL-based approaches.

The datasets used in these studies are very diverse, covering data types as varied as EEG, fMRI, eye-tracking, handwriting, digital cognitive tests, and multimodal data. Digital cognitive test-based datasets are the most commonly used type, as seen in studies such as Rello et al. (2020) [42] and Gasmi et al. (2024) [67]. These datasets are usually large-scale (thousands of participants) and include interactive behavioural features that are highly relevant for quantitative analysis. Neurophysiological data such as EEG and fMRI are generally more limited in number of subjects, but provide detailed features of brain activity and structure. EEG was used in several studies such as by Molina et al. (2022) [49] and Parmar et al. (2023) [54], with a relatively small number of participants (30-391), but still achieved high accuracy due to the good quality of signal features. Meanwhile, fMRI datasets (such as Zahia et al., 2020 [40] and Joshi et al., 2023 [55]) provide in-depth structural information, although they are usually expensive and complex to analyse.

Eye-tracking based datasets have also shown high effectiveness in dyslexia detection, for example the study of Raatikainen et al. (2021) which achieved an accuracy of almost 90% [47]. These data provide visual patterns of attention and eye movements that are closely related to reading difficulties, making them a rich source of information to support AI-based diagnosis. Handwriting datasets, such as those used by Zaibi et al. (2024) [62] and Kunhoth et al. (2023) [56], have also shown high effectiveness (up to 99% accuracy). The characteristics of these datasets include kinematic, temporal and spatial features, which help the AI recognise distinctive patterns in the writing of children with dyslexia, especially in fine motor tasks. Finally, multimodal data that integrates various data modalities (such as visual, EEG, MRI and cognitive) shows great potential in improving dyslexia detection accuracy. Alkhurayyif et al. (2024) used this approach with excellent results, confirming that the use of multimodal datasets could be a growing research trend in the future [69].

The effectiveness of using AI in detecting dyslexia is generally promising. Various studies have shown that AI algorithms are able to identify complex patterns with a high degree of accuracy, much more quickly and consistently than manual diagnosis approaches [74]. Studies using methods such as Random Forest, SVM, CNN, and multimodal approaches demonstrate the ability of AI to provide reliable detection results and operate at scale, enabling rapid and efficient screening across a wide range of populations. A key advantage of using AI in these clinical and educational contexts is its ability to overcome the challenges of manual diagnostic methods that tend to be slow, expensive, and prone to subjective bias [75]. AI models, especially those using gamification approaches and online interactive tests, can directly present objective and real-time screening results to users. This approach opens up great potential for early detection of dyslexia across different layers of the population, including areas with limited access to experts [76].

However, despite these advantages, existing studies also have some important limitations that need attention. One of the main limitations is the relatively small dataset size, especially in studies that utilise neuroimaging-based data such as EEG and MRI, as well as eye-tracking data. This limitation has a significant impact on the generalisability of AI models across broader populations, as well as introducing the risk of overfitting [77]. Future studies should endeavour to increase the sample size of participants to improve the robustness of results and external validity of AI models. Furthermore, many AI studies have not explicitly addressed the comorbidity aspect of dyslexia [78]. In fact, dyslexia often co-occurs with other developmental disorders such as ADHD, dyscalculia, or specific language impairment (SLI). This lack of consideration of comorbidity leads to challenges in distinguishing the distinctive patterns of dyslexia from other related disorders. Future research should focus more on integrating aspects of comorbidity in AI models, so that the resulting diagnosis becomes more specific, accurate and clinically relevant [79].

In terms of interpretability, the use of Deep Learning (DL) models, which have dominated recent studies, still faces a major challenge, namely limited transparency. These models are often referred to as “black boxes”, as it is difficult to explain the rationale behind the resulting decisions or classifications [80]. This poses a barrier to clinical and educational acceptance, as practitioners need an in-depth understanding of the model's decision bases in order for it to be implemented safely and effectively [81]. Therefore, the use of Explainable AI (XAI) approaches should be prioritised in future research. In the future, the direction of research should be towards utilising large-scale multimodal datasets, which combine various types of data such as EEG, MRI, eye-tracking, handwriting, and interactive linguistic data [82]. This multimodal integration will provide a more holistic picture of the characteristics of dyslexia from various neurocognitive, visual, motor and linguistic perspectives. Multicentre clinical trial-based external validation needs to be improved to ensure robust and relevant generalisability of the model across different populations [83].

In addition to multimodal datasets, further development and exploration of Large Language Models (LLMs) is also promising. Models such as GPT-3.5 Turbo show significant potential in processing complex and heterogeneous linguistic data, particularly in the context of dyslexia which is often closely related to language processing disorders. With additional training using dyslexia-specific datasets, LLM has the opportunity to improve its ability to provide in-depth analyses of the linguistic aspects of dyslexia, especially in multilingual and multicultural contexts [84]. Finally, future research should consider developing adaptive AI models that are able to dynamically adjust to changes in data and individual user characteristics [85]. AI methods capable of continuous learning or reinforcement learning can address this challenge, allowing the model to continuously update itself based on the latest data coming in from direct user interaction. As such, this adaptive approach will become an increasingly relevant trend to improve the effectiveness, sensitivity and accuracy of a more personalised and specific dyslexia diagnosis [86]. Furthermore, the integration of LLMs with multimodal learning systems could create hybrid frameworks that simultaneously analyze text, speech, and neural signals for more holistic detection outcomes. In the long run, such innovations may also contribute to the development of intelligent educational assistants that not only detect dyslexia but also provide personalized learning support and real-time feedback.

5. Conclusion

The findings indicate that applying AI for dyslexia detection holds great potential, particularly through Machine Learning (ML), Deep Learning (DL), multi-method approaches, and the adoption of Large Language Models (LLMs). Machine Learning, particularly Random Forest and SVM algorithms, are the top choices due to their computational efficiency and high accuracy. In addition, CNN-based Deep Learning models are also effective in analysing neuroimaging and eye-tracking data with an accuracy of more than 96%. However, limitations such as small datasets, lack of consideration of comorbidities, and low interpretability of DL models still pose challenges in clinical implementation. Furthermore, this study has a significant impact as it provides a comprehensive overview of the effectiveness and limitations of various AI methods in the early detection of dyslexia, as well as offering guidance for future research development. The results encourage researchers to focus attention on the development of large-scale multimodal datasets, further exploration of LLM for more complex linguistic analyses, and the utilisation of adaptive AI models capable of dynamically adjusting to individual characteristics. As such, this study makes an important contribution in encouraging the adoption of AI in the clinical and educational fields, to enhance early screening and more effective, rapid and accurate treatment of dyslexia.

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