Trusted GPT-5, ChatGPT and AI Detector tool by ZeroGPT

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AI/GPT Detector | ZeroCHAT-4 & 5 | Plagiarism Checker | AI Summarizer | AI Paraphraser | AI Grammar Check | AI Translator S

combinations via GridSearchCV. The ensemble model was more accurate than other individual classifiers. The study performed analyses on different disability related attributes (linguistic, memory, and visual discrimination), which allows for personalized risk assessment of dyslexia while in an educational setting.

Alluhaidan et al. (2024) [18] characterized a usage of artificial neural networks (ANN) with an online gamified test corpus to identify dyslexia in children. With appropriate preprocessing methods to deal with important issues such as class imbalance, noise, and outliers, they report a result of 97% accuracy, which is higher than reported state-of-the-art methods previously reported. The combination of gamified testing and artificial intelligence holds promise for large-scale, low-cost, easy to access, and effective early screening for dyslexia – although further studies to validate the work are needed. As an additional point, they envision

Detect Text

Upload File

14,984/15,000 Characters

Check 350,000 characters,

Upgrade Here

Your Text is Human written

0%
AI GPT*

The literature review examined a total of 19 studies that investigated dataset acquisition, preprocessing, feature extraction, and predictive performance. The authors address persisting concerns identified from the studies, including constrained dataset diversity, inconsistency in feature engineering, and issues regarding generalizability to different demographic information, and the authors highlight the development of complex deep learning models using multimodal data sources, including both structured and unstructured data sources. Furthermore, the authors advocate for standardized datasets that allow for reproducibility and accuracy in dyslexia detection models.

Aldehim et al. (2024) [3] created a convolutional neural network (CNN)-based presented a method for classifying dyslexia using handwriting images with strong performance in training (99.5% accuracy) and testing (96.4% accuracy) data. The proposed method demonstrated the capability of deep learning to recognize subtle features that can differentiate between the handwriting of dyslexic and non-dyslexic individuals. Furthermore, they applied the CNN model against the other state-of-the-art techniques and found the CNN model to be superior based on testing and training materials. The results highlight the potential practical utility of employing artificial intelligence analysis of handwritten text to aid in early detection and personalized interventions for children diagnosed with dyslexia.

To facilitate handwriting-based dyslexia detection, Robaa et al. (2024) [4] presented an explainable AI (XAI) framework employing transfer learning and transformer architectures. Their model demonstrated an accuracy rate of 99.65% and incorporated Grad-CAM visualizations to produce interpretable outputs highlighting handwriting features which contributed to the overall classification. This research underscored the importance of model transparency and interpretability for educators and clinicians to develop trust in an AI-based diagnosis. The framework's broad applicability across languages further creates relatedness for use within different linguistic populations, making it a globally applicable dyslexia screening solution.

Makhija proposed the DyslexiaAnalyzer, a tool based on explainable artificial intelligence that uses transfer learning with MobileNetV3 for dyslexia analysis from handwriting in 2025 [5]. The strategy is unique in that demonstrates the ability to perform explanation, where lightweight deep learning works together with Grad-CAM explainability to provide visual interpretations of the classifier's rationale. Overall, the models attained 96.54% accuracy, underscoring the potential for efficient and interpretable neural architectures in the processing of handwritten datasets that are complex. Makhija also provided valuable insights into future research, considering an interest in multimodal learning and real-time detection, and using AI-based architectural approaches to enhance inclusive educational systems.

Ramlan et al. (2024) [6] created a dataset of offline handwriting samples targeting children in

Malaysia who may have dysgraphia. The dataset consists of 249 samples divided into potential dysgraphia and low potential dysgraphia. The data were preprocessed into binary black-and-white images to facilitate computational analysis. This research provides an important resource for models being trained to classify dysgraphia and emphasizes the need for datasets that represent cultural and linguistic diversity within larger efforts to screen for learning disabilities using AI systems.

In a recent article, Rashid et al. (2023) [7] introduced a computational strategy, DYSIGN, to diagnose dyslexia and dysgraphia via handwriting quality assessment. The authors conducted a pilot study using handwriting samples from 25 children, aged 5–15 years, and examined participants' handwriting via scans. Once scanned, data were measured with feature extraction, and subsequently classifier models were assessed. Preliminary results showed approximately 80% accuracy, showing potential for future applications when workflows could be scaled. Traditional ways of diagnosing learning disabilities can limit accessibility, and this study intends to support the ultimate goal of using computation tools to create inexpensive and inclusive ways to screen for learning disabilities.

Patil et al. (2024) [8] developed an automatic dyslexia screening method employing children's handwriting in English when they produce handwritten text. They integrated a convolutional neural network (CNN) with bidirectional long short-term memory (Bi-LSTM) models to classify dyslexia using the handwriting text recognition (HTR) process. They trained classification models on the IAM dataset, achieving a text recognition accuracy of 95.6%, and they improved dyslexia classification metrics. Their CNN-BiLSTM integration makes it possible for the model to learn temporal features based on the sequence of child's handwriting, providing a timely, non-invasive approach to dyslexia screening as it relates to the students input and output in classroom settings.

Alkhurayyif and Sait (2023) [9] presented a novel approach to dyslexia detection. Utilizing image processing for handwriting enhancement, the deep learning-based dyslexia detection system (DDS) classified handwriting images into normal or abnormal (reversal) utilizing a large public dataset of images made available for academic research purposes. The model achieved a good accuracy of 99.2% and strong precision and recall compared to baseline benchmarks for testing data. The study suggests that DDS can be feasibly deployed in educational as well as clinical environments and suggests future extension toward multimodal dyslexia diagnostic systems, which may incorporate biomedical signals.

Dinusha et al. (2024) [10] introduced a machine learning-based technique to identify potential specific learning disabilities (SLDs), including dyslexia and dysgraphia. The model utilized six features extracted from static handwriting samples collected from children in an educational environment while examining various classifiers to identify the approach that achieved the highest accuracy rating. The random forest classifier model achieved the highest level of accuracy at 87.3%. Overall, findings indicated this approach may serve as a cost-effective and efficient potential approach for broad-scale educational screening specifically for early identification. The authors concluded that automated handwriting analysis offers great potential for large-group initial screening prior to a detailed psychological assessment.

Zaibi and Bezine (2024) proposed a machine learning-based intervention for early detection of learning disabilities (LDs) - dyslexia, dysgraphia and dyscalculia - via handwriting script analysis. Handwriting script was captured using the "Handyg23" dataset, which includes samples of handwriting from neurodegenerative and healthy control writers. Using principles of Beta-elliptic segmentation theory, the authors were able to extract temporal, spatial and kinematic features from the handwriting images. The machine learning system achieved an accuracy level of 99% with a gradient boosting classifier. As a whole, this research project represents a significant advancement over traditional, manual diagnostic approaches by providing a highly accurate, automated and non-intrusive option for early LD detection.

KT (2023) [13] proposed DxDetekt, a method for detecting dyslexia through ensemble-based Directed Acyclic Graph (DAG) networks applied to handwriting images. The authors evaluated different configurations of DAG networks (for example - DAG-1, DAG-2, DAG-3, DAG-4) and achieved a training accuracy of 99.01% and a test accuracy of 89.68%. The authors noted the effectiveness of using skip connections in DAG networks, improving the representation of handwriting features, thereby improving the detection of handwriting features relating to dyslexia. The proposed system offers rapid, objective and reliable automated screening for dyslexia.

In their 2023 study, Devi and Kavya [14] proposed a deep learning-based paradigm for the purpose of detecting dysgraphia based on a Kekre-Discrete Cosine Transform with Deep Transfer Learning method (K-DCT-DTL). The model classifies dysgraphia based on handwritten and geometric features and achieved a maximum accuracy of 99.75%. K-DCT-DTL demonstrated improved performance distinguishing dysgraphic handwriting patterns in comparison to conventional ML and DL approaches. The authors found that mathematical transformations combined with deep learning may provide accurate and high precision when identifying dysgraphia.

Kunhoth et al. (2025) [15] presented the inaugural multimodal dataset for grading severity in Developmental Dysgraphia, comprising online handwriting (i.e., digitized pen trajectory) and offline handwriting data from 113 children. The dataset incorporated writing tasks at the letter level, word level, pseudoword level, and sentence level. The classification system proposed in the study provided evidence of conference-room identity and multi-modal fusion methods that used meta-learning and weighted voting demonstrated a recall rate of 85.67% in classification–a performance level that improved upon the performance rates of models developed using single modalities alone. This research delineates the need for severity assessment frameworks in developmental dysgraphia and will provide a basis for personalized dysgraphia severity assessments and intervention tracking.

In the study conducted by Babu (2024) [16], an ensemble-learning approach was developed to predict dyslexia using the PLOS ONE Dyslexia Dataset. It utilized a variety of machine learning (ML) algorithms such as Decision Trees, Random Forests, and Support Vector Machines, combined by optimization using hyperparameter combinations via GridSearchCV. The ensemble model was more accurate than other individual classifiers. The study performed analyses on different disability related attributes (linguistic, memory, and visual discrimination), which allows for personalized risk assessment of dyslexia while in an educational setting.

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Doshi et al. (2023) [19] described similar development of convolutional recurrent neural network (CRNN)-based models for handwritten text aimed at potential dysgraphia predictions. The use of CRNN approaches enhances the automation of a manual screening approach and allows educators and parents to diagnose potential handwriting based learning disabilities. The CRNN structure was effective in capturing both spatial and sequential handwritten text patterns by combining CNN with recurrent architectures. The utility of the technology was further noted in the large, non-invasive nature of possible assessments for handwriting difficulties associated with dysgraphia.

The work of Alqahtani et al. (2023) [20] involved a hybrid CNN-SVM and CNN-RF framework for dyslexia detection utilizing a handwriting image dataset of 176,673 samples. The feature extraction was accomplished with CNN models and SVM and Random Forest were used for classification. The hybrid CNN-SVM method obtained 99.33% accuracy, performing best among the configurations investigated. The study highlights a successful combination of ML and DL in improving accuracy for handwriting-based dyslexia diagnostics.

In another study, Patil et al. (2024) [21] explored deep learning methodologies in anticipation of learning disabilities through an analysis of handwritten text. The authors compared a handful of diagnostic modalities (handwriting recognition, games, EEG, and brain imaging) and found handwriting to be the most accurate diagnostic route, and also scalable. The anticipated system distinguished between dyslexic and non-dyslexic handwriting using the IAM dataset and deep neural networks, while supporting handwriting-based ML modeling as a key method in early LD detection.

Alzahrani and Algahtani (2025) [22] introduced a Weighted Ensemble Learning XGBoost (WEL-XGB) model with the goal of being used for diagnosing specific learning disabilities (SLDs) — dyslexia and dysgraphia. They used data from individualized reading and writing assessments that included performance scores and completion time. The WEL-XGB model demonstrated 98.7% for dyslexia and 99.08% accuracy for dysgraphia. In addition to providing diagnostic information about a learner's condition, the WEL-XGB model prompts feedback that educators can use to improve methods that incorporate dyslexia or dysgraphia as areas of risk for learners. Therefore, the WEL-XGB model showed that it could be used as a significant educational and assessment tool.

Chowdhury et al. (2025) [23] developed a dual-modality ML framework that utilized handwriting and EEG signals to detect and monitor motor dysgraphia as early as possible. The handwriting data characteristics included—pressure, pen trajectory, and azimuth—combined with the spectral density (PSD) signal features took information about brain neurophysiology and learning difficulties and informed ML models of mapping dysfunctional motor process to patterns in brain activity. The proposed framework gives an accurate, non-invasive diagnostic pathway connecting cognitive neuroscience with AI-informed educational practice.