

A Multimodal Webcam-Based Approach for the Early-Stage Screening of Dyslexia

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Abstract— *Dyslexia is a learning disability that affects reading, writing capabilities, and fluency of an individual. Early screening in resource-constrained settings often requires specialized hardware, expert supervision, and lengthy, expensive assessment processes. Due to technological advancements today, machine learning models are used for detecting and flagging early signs of dyslexia based on eye gaze tracking and handwriting analysis. Existing technology-aided systems are single modal, using either handwriting or eye gaze tracking movements. These systems use special infrared eye trackers for eye gaze-based systems, which are usually expensive, and they utilize eye-gaze patterns like fixation duration, saccade length, and regressions during reading to differentiate between dyslexic and non-dyslexic individuals. Handwriting-based systems analyze structural patterns of letters and writing inconsistencies such as spelling and phonetic errors, using deep learning and machine learning models such as SVM and CNN. This paper presents a systematic review of existing dyslexia screening systems and proposes a novel multimodal approach utilizing both handwriting-based and eye-gaze tracking analysis modules, using a standard webcam and eye-gaze tracking libraries instead of specialized infrared trackers.*

Keywords— *Dyslexia screening, eye-gaze tracking, handwriting analysis, multimodal machine learning, webcam-based approach.*

I. INTRODUCTION

Dyslexia is a neurodevelopmental learning disorder that affects approximately 5–10% of the global population. It is characterized by difficulties in reading fluency, spelling accuracy, and written language processing despite normal intelligence and adequate educational opportunities. Early detection of dyslexia is crucial, as timely intervention during the early learning years—which are critical for an individual's growth—can significantly improve reading skills, academic performance, long-term educational outcomes, and overall cognitive development.

However, traditional diagnostic processes include standardized paper-based assessments, clinical interviews, and specialized infrared eye-tracking systems that serve as substantial barriers in terms of cost, accessibility, and scalability. Diagnosis typically requires trained specialists, expensive equipment, and lengthy evaluation protocols, making it inaccessible for resource-constrained environments.

Due to advances in machine learning and computer vision, new approaches for dyslexia screening using behavioral factors such as eye movements and handwriting patterns have emerged. Studies have shown that dyslexic readers typically exhibit longer and more frequent fixations, shorter saccades, and increased regressions while reading, along with irregular gaze trajectories. Handwriting can reveal characteristic indicators, including letter reversals, inconsistent spacing, and spelling errors.

Although prior work has explored eye-tracking or handwriting analysis independently, there remains a need for a unified, low-cost, multimodal system that operates with only a standard webcam and is practical for deployment in everyday resource-constrained classroom and home environments.

This paper presents a web-based multimodal approach to flag early signs and risks of dyslexia using webcam-based eye movement tracking and handwriting analysis. The proposed system leverages WebGazer.js for eye tracking and MobileNetV3 for handwriting feature extraction, with a weighted voting ensemble combining predictions from multiple modalities.

II. LITERATURE SURVEY

Asvestopoulou et al. [1] introduced DysLexML, a machine learning-based screening system for detecting developmental dyslexia using eye-tracking data. A field study in Greece involved 69 children aged 8.5–12.5 years, including 32 diagnosed

with dyslexia. Linear SVM combined with LASSO achieved the best results, reaching 97.1% accuracy on difficult text and 87.9% on easier text.

Cogan, Ngo, and Roantree [2] proposed a non-invasive approach for early dyslexia detection combining eye-tracking data with machine learning. Using the Provo Corpus dataset of 84 native English speakers, a Random Forest classifier achieved 88.58% accuracy and an AUC of 0.96.

Ribeiro, Brandl, and Sogaard [3] presented WebQAmGaze, a multilingual webcam-based eye-tracking dataset collected from 600 participants across English, German, Spanish, and Turkish using WebGazer. Random Forest models combining gaze and text features demonstrated that webcam-based eye tracking can capture cognitive reading patterns.

Ikermane and El Mouatasim [4] proposed a low-cost dyslexia screening approach for Arabic readers using webcam-based eye tracking and deep clustering. A study of 61 Moroccan students analyzed reading behavior captured via WebGazer, identifying high-risk, moderate-risk, and typical readers.

Vaitheeshwari et al. [5] presented a VR-based dyslexia diagnostic framework combining eye-tracking, machine learning, and NLP. Using an HTC Vive Pro with a Tobii eye-tracker, a hybrid model integrating BERT, CNN, and DNN achieved 98% accuracy.

Vajs et al. [6] proposed an accessible dyslexia detection method using interpretable eye-tracking features with real-time reading feedback. A study of 30 Serbian children achieved up to 88.9% accuracy.

Jaiyeola et al. [7] investigated webcam-based eye tracking to model attention and comprehension in neurotypical and neurodivergent learners. Gaze data from 354 participants was collected using WebGazer, with SHAP analysis revealing distinct predictive features across populations.

Isa et al. [8] presented an automated system for early dyslexia detection using handwriting images from primary school children aged 7–12. An ANN (MLP) classifier categorized children into risk and low-risk groups.

Benfatto et al. [9] examined eye tracking as an objective method for early dyslexia screening in children. Using infrared eye tracking on 185 Swedish children aged 9–10, an SVM model achieved 95.6% accuracy.

Prabha and Bhargavi [10] proposed a machine learning framework for dyslexia detection based on fixation and saccadic eye-movement patterns. A Hybrid SVM–PSO model achieved 96% accuracy.

Vajs et al. [11] presented a cross-lingual dyslexia detection framework using eye-tracking image encoding and convolutional autoencoders, achieving over 80% accuracy across datasets.

Isa et al. [12] evaluated multiple CNN architectures for detecting dyslexia symptoms from children's handwriting images. All models achieved validation accuracies around 86–87%.

Garg and Pratap [13] reviewed advances in AI-based handwriting analysis for multilingual dyslexia detection, highlighting that CNN-based models sometimes exceed 97% accuracy.

Jaiyeola et al. [14] examined whether webcam-based eye tracking can capture cognitive differences between neurodivergent and neurotypical learners during online reading tasks.

Robaa et al. [15] presented an explainable AI framework for dyslexia detection using handwriting analysis, combining transfer learning with MobileNetV3 and transformer-based models, achieving 99.65% accuracy.

Nerusil et al. [16] presented a machine learning–based method for detecting dyslexia using eye-tracking data, with an SVM classifier achieving high accuracy.

Zhang and Zhou [17] proposed a dyslexia detection system using computer vision–based eye tracking instead of specialized hardware, achieving 89.7% accuracy.

Alqahtani, Alzahrani, and Ramzan [18] proposed hybrid deep learning–machine learning models for dyslexia detection from handwriting images. The CNN-SVM model achieved the highest accuracy of 99.33%.

Rosli et al. [19] presented a CNN-based transfer learning approach for dyslexia handwriting recognition using a modified LeNet-5 architecture, achieving 95.34% accuracy.

Hussein et al. [20] proposed a CNN-based framework for diagnosing dyslexia using speech signals transformed into spectrogram images, achieving up to 99% accuracy.

III. ANALYSIS TABLE

TABLE 1
SUMMARY OF REVIEWED STUDIES ON DYSLEXIA SCREENING

Sr. No.	Paper Title (Year)	Features Used	Technology Used	Accuracy
1	DysLexML: Screening Tool for Dyslexia Using Machine Learning (2019)	Mean/Median saccade length, short forward movements, multiply fixated words	Linear SVM, LASSO Regression	97.10%
2	Developing a Dyslexia Indicator Using Eye Tracking (2025)	First saccade amplitude, regression count, fixation count, saccade duration	Random Forest	88.58%
3	WebQAmGaze: Multilingual Webcam Eye-Tracking Dataset (2024)	Fixations, target fixation ratio, reading time	Random Forest	74%
4	Dyslexia Deep Clustering Using Webcam Eye Tracking (2023)	Fixations, fixation duration, saccade duration, regression count	K-means Clustering	65%
5	Dyslexia Analysis and Diagnosis Based on Eye Movement (2024)	Fixation duration/count, saccade frequency/direction, gaze patterns	DNN, BERT	DNN:94%, BERT:92%
6	Accessible Dyslexia Detection with Real-Time Reading Feedback (2023)	Vertical alteration score, SI event detection, reading time	Linear Regression, SVM	88.90%
7	One Size Does Not Fit All: Webcam Eye Tracking for Neurodivergent Learners (2025)	Fixations, gaze behavior, word/syllable count	WebGazer.js, NLTK	70–79%
8	Automated Detection of Dyslexia from Handwriting Images (2019)	Handwriting patterns (letters: b,c,f,p; numbers: 2,5,6,7)	OCR, ANN	OCR:73.33%, ANN:70.83%
9	Screening for Dyslexia Using Eye Tracking During Reading (2016)	Fixations, saccade durations/length	SVM	95.60%
10	Predictive Model for Dyslexia from Fixations and Saccades (2020)	Fixations, saccades, blinks, repeat fixations	Hybrid SVM-PSO	96%
11	Eye-Tracking Image Encoding for Cross-Lingual Dyslexia Detection (2022)	Gaze complexity range	Logistic Regression, SVM, RF	82.90%
12	CNN Comparisons for Dyslexia Handwriting Classification (2021)	Handwriting patterns, letter inversion/reversal	CNN	86%
13	Dyslexia Across Languages: Handwriting-Based Detection (2025)	Handwriting markers, language-specific indicators	CNN, SVM	99.20%
14	Webcam Eye Tracking to Understand Neurodivergence (2025)	Gaze count, fixations, reading time	WebGazer.js, RF, Logistic Regression	60%
15	Explainable AI in Handwriting Detection for Dyslexia (2024)	Normal/reversed/corrected letters, stroke patterns	Grad-CAM, MobileNetV3	99.65%
16	Eye Tracking Based Dyslexia Detection Using Holistic Approach (2021)	Fixation count/duration, saccade length, regression frequency	SVM	>90%
17	Dyslexia Detection Based on Eye Tracking (2022)	Reading speed, saccade length/duration	Computer vision, TOPSIS	89.70%
18	Detection of Dyslexia Through Handwriting Using Hybrid AI (2023)	Handwriting image features, stroke patterns, letter reversal	CNN, RF, SVM	CNN-SVM:99.33%
19	CNN Transfer Learning for Dyslexia Handwriting Recognition (2021)	Handwriting patterns, letter reversal, stroke structure	Modified LeNet-5	95.34%
20	Classification of Dyslexia Using Deep Learning (2024)	Spectrogram features from speech	2D-CNN	99%

IV. RESULTS

According to the research reviewed, machine learning-based approaches have reported high accuracies; however, performance varies depending on dataset size, model used, and feature selection. Reported accuracies range between 70% and 95%.

Eye-Tracking Based Systems:

- Systems using specialized eye-trackers with machine learning (e.g., DysLexML) achieved accuracy of 97.1%
- Approaches using simple ML models (SVM, Random Forest) with webcams and libraries like WebGazer.js achieved accuracies between 70% and 90%

Handwriting-Based Systems:

- Show generally moderate to high accuracy (70–90%), suitable for early-stage detection
- MobileNetV3-based CNN model achieved the highest accuracy of 99.65%
- Hybrid CNN-SVM models reached 99.33% accuracy
- Transfer learning CNN models achieved 95.34% accuracy

Speech-Based Systems:

- Spectrogram-based CNN frameworks reported up to 99% accuracy

These studies demonstrate diverse AI-based approaches for dyslexia detection using eye-tracking, handwriting, and speech analysis. Overall, deep learning significantly enhances objective, early, and accessible dyslexia screening across multiple modalities.

V. RESEARCH GAPS

Analysis of existing dyslexia detection systems reveals several significant research gaps:

Gap	Description
Gap 1	Many eye-tracking approaches rely on small, language-specific, or laboratory-controlled datasets, limiting cross-linguistic generalizability
Gap 2	Webcam-based systems improve accessibility but often report lower accuracy, indicating a trade-off between affordability and precision
Gap 3	No unified multimodal framework robustly integrates eye-tracking, handwriting, and speech signals across scripts and cultures
Gap 4	Handwriting-based deep learning models lack clinical validation, balanced datasets, and real-time deployment testing
Gap 5	Explainability remains inconsistent; most deep learning models lack cognitive interpretability linked to dyslexia theories
Gap 6	Few studies address longitudinal monitoring, early pre-reading detection, or integration into classroom ecosystems

Overall, despite high reported accuracies, there remains a gap in developing **scalable, explainable, multimodal, cross-linguistic, and clinically validated** dyslexia screening systems that balance accessibility with diagnostic reliability.

VI. PROPOSED SOLUTION

This study proposes a **multimodal baseline screening system** for the early identification of dyslexia, addressing the research gap of lacking a dedicated, scalable pre-clinical screening tool that can be deployed in real-world environments such as schools and homes.

6.1 System Overview

The system integrates two complementary modalities:

Modality	Components	Features Extracted	ML Model
Eye-Gaze Tracking	Three reading tasks (syllable-based, normal text, pseudo-text) via WebGazer.js	Regressions, saccade lengths, fixation patterns	CatBoost
Handwriting Analysis	Uploaded handwritten text image	Structural patterns (letter reversals, irregularities), spelling/grammatical errors	MobileNetV3 + Random Forest

6.2 Key Features

- **Calibration Phase:** Prior to reading tasks, individuals fixate on randomly appearing dots to ensure accurate gaze-coordinate capture under varying environmental conditions
- **Reading Tasks:** Syllable matrix task (phonological processing), normal passage reading (fluency), pseudo-text task (phonetic decoding)
- **Handwriting Pipeline:** Structural analysis via MobileNetV3; OCR + NLP for spelling/grammar analysis
- **Ensemble Fusion:** Weighted voting ensemble to generate final confidence score and detailed report

VII. CONCLUSION

The proposed multimodal approach aims to provide an accessible, reliable, and technology-driven solution for the early screening of dyslexia. By leveraging eye-tracking-based reading assessments and handwriting analysis with advanced machine learning models, the system can identify potential signs of dyslexia in an efficient and non-invasive manner.

The structured flow—from onboarding and calibration to screening tests and intelligent analysis—ensures both personalization and accuracy in results. Unlike traditional methods, which are often time-consuming and require expert intervention, this approach offers a scalable, automated, and user-friendly platform that can reach a wider population, including children at an early stage of their learning journey.

With its ability to generate interpretable reports and flag possible cases, this project bridges the gap between existing research-based models and practical, real-world applications. Ultimately, it has the potential to make a significant impact in educational and healthcare domains by assisting teachers, parents, and professionals in providing timely support and interventions for individuals with dyslexia.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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