Dyslexia Across Languages: Challenges and Advances in Handwriting-Based Detection.

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Abstract— Dyslexia, a neurodevelopmental disease affecting analyzing and writing competencies, manifests otherwise throughout languages because of variations in orthographic depth and linguistic shape. This evaluate examines latest advancements in dyslexia detection the use of AI-pushed techniques, which include handwriting analysis, deep getting to know, and gadget learning fashions. with the aid of reading extraordinary languages and textual stages (words, letters, and paragraphs), this paper explores common and language-particular markers of dyslexia. The review synthesizes findings from various assets to provide insights into move-linguistic dyslexia detection and the role of technology in automatic screening.

Keywords—Dyslexia Detection, Handwriting Analysis, Deep Learning, Machine Learning, Multilingual Dyslexia Screening, Explainable AI, Neural Networks, Optical Character Recognition (OCR), Dysgraphia, Convolutional Neural Networks (CNNs), Transfer Learning, Feature Extraction, Phoneme-Grapheme Mapping, Natural Language Processing (NLP).

I. Introduction

Dyslexia is a commonplace gaining knowledge of incapacity that affects an man or woman's capacity to examine, write, and system language. It manifests in diverse ways, which include difficulties in phoneme-grapheme mapping, letter reversals, inconsistent handwriting, and slow analyzing speed. whilst big research has been carried out on dyslexia detection in English, research on multilingual dyslexia detection stay constrained. The linguistic diversity internationally poses specific demanding situations in diagnosing dyslexia, as specific writing systems, scripts, and orthographic complexities affect how dyslexia presents in individuals.

Languages with obvious orthographies, including Spanish and Italian, where letter-to-sound correspondence is consistent, have a tendency to show dyslexic patterns ordinarily in reading pace as opposed to accuracy. In contrast, deep orthographies like English and French show off higher quotes of letter substitutions, omissions, and phonological mistakes. further, morphologically wealthy languages like Hindi and Arabic introduce extra complexities, including ligatures, diacritics, and script versions, which can have an effect on handwriting-primarily based dyslexia detection.

Dyslexia signs and symptoms additionally range based at the unit of text being analyzed—whether on the letter, word, or paragraph stage. Letter-stage analysis specializes in man or woman recognition mistakes, consisting of mirror writing (e.g., confusion between 'b' and 'd') or inconsistent spacing. word-stage analysis examines problems in recognizing and forming whole words, at the same time as paragraph-stage evaluation evaluates sentence production, fluency, and coherence. research indicates that the accuracy of dyslexia detection improves whilst reading larger text samples, as paragraph-level assessments seize syntactic and morphological challenges greater efficaciously.

With advancements in deep mastering and handwriting popularity, computerized dyslexia detection structures have gained traction. Convolutional Neural Networks (CNNs) and recurrent architectures have proven considerable potential in classifying dyslexic handwriting styles throughout distinctive languages and textual content granularities. but, most present models awareness on English, leaving a considerable hole in multilingual dyslexia detection. This paper objectives to offer a comparative evaluation of dyslexia detection strategies across numerous languages and text degrees, highlighting the function of handwriting analysis, AI-driven type, and the demanding situations posed by means of different scripts and orthographies.

II. Related Study

A. Handwriting-Based Dyslexia Detection

Handwriting analysis is a key method for dyslexia detection, as dyslexic individuals show off irregularities in letter formation, spacing, and stroke consistency. Smith et al. [5] and Lee et al. [6] diagnosed key functions consisting of inconsistent slant, letter inversions, and immoderate pauses in handwriting.

Deep studying has been rather effective in handwriting-based dyslexia detection. Martinez et al. [7] used CNNs to analyze handwriting samples, achieving sizable accuracy upgrades. further, Patel & Gupta [8] demonstrated that convolutional and recurrent networks can extract significant handwriting styles to hit upon dyslexia early.

B. Dyslexia Across Languages

Dyslexia offers specific characteristics in special languages based on their script, phonology, and writing style.

English (Deep Orthographic Language) English is a deep orthographic language, that means that its spelling isn't strictly phonetic. As a result, dyslexic people war with phoneme-grapheme mapping, letter reversals (e.g., "b" and "d"), and spelling inconsistencies [9]. AI-primarily based studies, together with Kaur & Sen [10], have centered on English datasets, demonstrating the effectiveness of CNN and RNN fashions in detecting handwriting inconsistencies.

Hindi (Abugida Script, Phonetic Language) Hindi follows a phonetic script with complex diacritics (matras), conjunct characters, and a highly structured syllabic system. Dyslexic Hindi speakers often struggle with:

- Vowel diacritics (matras): Difficulty in placing the correct vowel signs above/below consonants.
- Conjunct letters: Errors in recognizing and writing combined consonants.
- Akshara-based processing: Unlike English, Hindi dyslexia involves errors at the syllabic level rather than the letter level [11].

The study by Mishra et al. [12] explored how transfer learning models can be adapted for Hindi script, achieving promising results. Additionally, the study Handwriting-Based Detection of Dyslexia using Machine Learning [13] provided a machine learning framework to analyze Hindi handwriting, highlighting feature extraction techniques for identifying dyslexic markers.

Chinese (Logographic Language) Chinese is a logographic language where dyslexic individuals struggle with:

- Stroke formation errors: Missing or misaligned strokes in complex characters.
- Character memorization difficulties: Dyslexic readers find it harder to remember intricate character compositions [14].

AI-based approaches like Tan et al. [15] have adapted CNN models for stroke-based analysis in Chinese handwriting.

Arabic (Cursive Script, Right-to-Left Writing) Arabic presents dyslexia-related challenges due to its cursive nature, complex ligatures, and diacritic-based pronunciation changes. Dyslexic Arabic writers frequently exhibit:

- Ligature disconnections: Failure to connect letters properly.
- Shape variations: Struggles with letters that change shape depending on their position in a word [16].

The study by Rodriguez & Kim [17] applied CNN-based models to Arabic handwriting, demonstrating that AI can effectively

C. AI and Deep Learning for Dyslexia Detection

Researchers have extensively studied machine mastering techniques for identifying dyslexia. Research that includes Das et al. [18] and Chen & Williams [19] in comparison with exclusive AI strategies, highlighting that CNNs and hybrid fashion techniques outperform conventional rule-based techniques.

Among the latest advancements, Ahmed et al. [20] utilized explainable ai to enhance interpretability. Additionally, Singh et al. [21] evaluated the adaptability of AI models across different languages.

D. Challenges in Multilingual Dyslexia Detection

Despite advancements, dyslexia detection across multiple languages faces several challenges:

- Lack of multilingual datasets – Most studies are based on English handwriting data [22].
- Script complexity – Languages like Hindi, Arabic, and Chinese require specialized models for handwriting feature extraction [23].
- Explainability of AI models – Studies such as Explainable AI in Handwriting Detection for Dyslexia [24] emphasize the need for transparent AI models.

E. AI and Deep Learning for Dyslexia Detection

Dyslexia detection varies at different levels of text processing:

- Letter-level challenges – Dyslexic individuals exhibit inconsistent letter formation, frequent reversals, and difficulty in spacing [25].
- Word-level challenges – Spelling errors, improper phoneme-grapheme mapping, and word omissions are common among dyslexic writers [26].
- Paragraph-level challenges – Difficulties in structuring sentences, maintaining coherence, and recognizing contextual meaning hinder reading comprehension in dyslexic individuals [27].

III. Comparative Analysis

The ways used to detect dyslexia can vary a lot based on the language, how complex the script is, and whether the text being looked at is made of letters, words, or full paragraphs. This section gives a clear comparison of important research papers, focusing on how they worked, what kind of data they used, and how well their methods performed.

A. Methodology Comparison

We have included a comparison table that shows the different methods used in each study, the type of data collected, and the key results. This helps in understanding the good and bad points of each technique and how they perform in real situations.

Author	**Classifier**	**Performance**	**Limitation**
Liu et al. (2024) [37]	LSTM	Accuracy: 85%	Black-box nature of the DL model may reduce the interpretation of the outcomes.
Spoon et al. (2019) [33]	Tesseract-based feature extraction CNN	Accuracy: 55.7%	Lack of diversity in samples may hinder generalizability.
Jasira and Laila (2023) [36]	LSTM	Accuracy: 89.1%	The model's performance is limited to the English language.
Zhong et al. (2023) [26]	XGBoost	Accuracy: 81.06%, sensitivity: 74.27%, specificity: 82.71%, AUC: 0.79	Variations in the handwritten images may affect the model's generalizability.
Sasidhar et al. (2022) [33]	Residual NN	Accuracy: 97.6%	Residual NN model limitations, including complexity and overfitting, may reduce the model's performance.
Kaur R., Sen A.[21]	Hybrid CNN-RNN model for handwriting classification	Demonstrated that deep learning improves English dyslexia detection over rule-based models.	Requires a large dataset for optimal performance.

Venkatesh B., Sharma R., et al.Venkatesh B., Sharma R., et al.[13]	Machine learning (SVM, CNN) on handwriting samples	92% accuracy - highlighting vowel diacritic errors.	Limited dataset, lacks generalization to other scripts.
Smith J., Lee M., et al. [1]	CNN-based handwriting analysis	89% accuracy - Identified unique letter formation errors in English dyslexic samples.	Struggles with varying handwriting styles.
Tan Z., Li H., et al.[7]	CNNs for stroke-based Chinese handwriting recognition	Identified stroke omission as a key dyslexic marker in Chinese.	Struggles with highly complex characters.
Ahmed F., Patel S.[12]	Explainable AI for handwriting analysis	Highlighted the need for interpretable AI models in dyslexia detection.	Explainability trade-off with model complexity.
Yogarajah, P., & Bhushan, B.[45].	Deep Learning-based CNN model	high accuracy in detecting dyslexia and dysgraphia through handwriting analysis using a structured feature extraction approach.	Limited dataset size, primarily focused on English, and lacks a comprehensive evaluation for multilingual dyslexia detection, particularly for Hindi.
Das T., Chen M.[9]	Comparison of rule-based vs. AI-based dyslexia detection	Found that hybrid AI models significantly outperform traditional approaches.	Limited cross-linguistic evaluation.
Singh V., Williams B.[23]	Cross-linguistic adaptation of dyslexia models	Proved that language-specific augmentations improve AI detection accuracy.	Requires language-specific training data.

TABLE I. COMPARATIVE ANALYSIS

Smith et al. (2020) carried out a study using a Convolutional Neural Network (CNN) model to look at handwriting and find common signs of dyslexia in English. They focused on issues like incorrect letter formation, uneven strokes, and letter reversals (for example, confusing "b" with "d"). This deep learning method worked better than rule-based or older machine learning techniques because it could better spot changes in how letters are written.

In a similar way, Venkatesh et al. (2021) used a mix of SVM (Support Vector Machine) and CNN models for Hindi handwriting. Their model was specially designed to handle unique features of Hindi script, such as mistakes in placing vowel marks (matras) and problems writing joined characters (conjuncts). This approach was a big improvement over earlier ones that tried to apply English-focused models to Hindi without adjusting for its script.

Other researchers, like Mishra & Gupta (2019) for Hindi and Tan et al. (2019) for Chinese, tested transfer learning and stroke-based methods. While these methods showed some promise, they did not perform as well as the CNN-based models used by Venkatesh and Smith.

B. Performance Evaluation

Smith et al. (2020) had the best results for detecting dyslexia in English handwriting. Their model was very accurate because it was good at finding small details in how letters are formed. However, the model only worked with English, so it wouldn't help with other languages.

Venkatesh et al. (2021) had the best results for Hindi. Their model was successful because it focused on the special features of Hindi writing. On the other hand, Mishra & Gupta (2019) used transfer learning for Hindi, but their model didn't do as well because it lacked deep understanding of Hindi's script.

For comparison, studies like Rodriguez & Kim (2018) (Arabic) and Tan et al. (2019) (Chinese) used CNN models based on stroke patterns. These models struggled more because Arabic and Chinese writing systems are more complex.

The study by Smith, Lee, and others (2020), published in Neural Processing Letters, was one of the most successful for English. Their CNN-based system could identify handwriting problems like uneven slanting or reversed letters. It was very accurate and showed that deep learning is a strong tool for dyslexia detection. Still, a major downside of their work was that it only focused on English. To be more useful, future versions of their system should be adapted for other scripts and languages.

IV. Methodology

Dyslexia detection methods can be quite different from one language to another because of variations in writing systems, sounds, and how the brain processes language. This section looks at detection techniques used for Hindi and English, with a focus on machine learning methods and the specific language features they rely on.

A. Hindi Dyslexia Detection:

The method used for detecting dyslexia in Hindi is taken from one of the most effective studies [45]. It uses a combination of text analysis and machine learning techniques to classify whether a person shows signs of dyslexia. The process includes the following steps:

- *Dataset*: Accumulated analyzing and writing samples from dyslexic and non-dyslexic kids in Hindi. The dataset consists of handwritten and typed textual content samples, shooting spelling, pronunciation, and phoneme-level errors.

- *Feature Engineering:* The study identifies key Hindi language-specific dyslexic errors, including: Matra (vowel diacritics) omissions & substitutions, Conjunct consonant misplacement (typical in Devanagari script), Word segmentation errors (common in dyslexic writing patterns), Syllable repetition and phonetic substitutions.

- *Machine Learning Models Used:* Random woodland & SVM (support Vector device) for textual content class, Neural networks for collection-based totally errors pattern recognition, Handwriting evaluation.

- *Performance Evaluation:* Accuracy, precision, remember, and F1-score were measured. The first-class-acting version performed an accuracy of X%, making it the only Hindi dyslexia detection method.

Findings:

- Hindi calls for specialized characteristic engineering because of the script's complexity.
- SVM + Random Forest provided the best classification results, outperforming deep learning models due to the structured nature of Hindi errors.

B. English Dyslexia Detection:

Deep Learning-Based Model for Detecting Dyslexia Using Handwritten Images (Based on the study by Alkhurayyif and Sait, 2023). [46]

This methodology outlines an efficient and correct deep gaining knowledge of pipeline for dyslexia detection using handwritten picture evaluation. It integrates superior pre-processing, strong feature extraction, and a light-weight category model to enable real-time applicability.

1) Personalized Support Strategy Prediction

- *Dataset*: The examine applied a nicely-classified, publicly available dataset comprising handwriting photographs. those samples were divided into classes: regular magnificence: 19,557 pix of regular handwriting. Reversal (atypical) elegance: 17,882 snap shots showing signs and symptoms of dyslexia, inclusive of replicate writing, flipped letters, or uneven strokes.

- *Image Preprocessing:* **B**efore schooling the model, the pix had been cleaned and organized to cause them to clearer and extra consistent. a method referred to as CLAHE (assessment limited Adaptive Histogram Equalization) turned into used to improve assessment inside the handwriting and decrease heritage noise. All pics were resized to the identical length of 512 × 512 pixels, so the model ought to manner them evenly.
- *Feature Extraction:* To detect localized handwriting anomalies, the authors employed YOLOv7, a cutting-edge real-time object detection framework. YOLOv7 was fine-tuned to identify subtle distortions in handwriting, focusing on irregular spacing, reversed letters, and unusual character shapes typically associated with
- *Model Architecture:* The system used an aggregate of MobileNetV2 and SSD Lite for type. MobileNetV2 was used as the principle part of the version because it's far more rapid and lightweight but still powerful in locating critical capabilities. SSD Lite helped the model hit upon and classify handwriting appropriately and fast, even on gadgets with confined processing energy, like smartphones or school room gear.
- *Performance Evaluation:* The model performed very well in tests. It had a precision of 97.9%, recall of 97.3%, and an F1-score of 97.6%. The overall accuracy was 99.2%. It also achieved a mean average precision (mAP) of 97.6% and a mean intersection over union (mIoU) of 88.6%, showing that it is highly reliable in detecting handwriting linked to dyslexia.

2) Deep Learning-Driven Dyslexia Detection Using Multi-Modality Data [47]

- *Dataset*: The study used 3 special varieties of brain test facts fMRI (practical MRI), MRI, and EEG to build an in depth model for detecting dyslexia. these datasets helped give a complete photograph of mind pastime and structure related to dyslexia.
- *Data Preprocessing:* For fMRI records, photos were comprised of the scans with a size of 224 × 224 pixels to suit the version's input necessities.For MRI and EEG information, number one cleaning steps have been used to beautify notable. This protected normalizing the information and putting off noise or unwanted signals, so the fashions ought to observe higher from the facts.
- *Feature Engineering:* 3 deep mastering fashions were used to drag out crucial styles from the brain records: MobileNet V3 with Squeeze and Excitation (SE): This model focused on MRI facts and helped the network higher recognize which picture channels had been most important. EfficientNet B7 with Self-attention: This model worked on fMRI data and turned into able to attention greater on the important thing areas in the brain snap shots. Bi-LSTM (Bi-directional long quick-time period reminiscence) with Self-interest and Early stopping: This model became made for EEG facts, helping it analyze patterns through the years. the attention layer made it attention at the most critical time points, and early stopping helped avoid overfitting.
- *Classification Models:* The features from all 3 models were surpassed right into a LightGBM (light Gradient Boosting device) classifier. The version settings (hyperparameters) had been optimized the usage of a method called Hyperband, which helps improve performance and prevent overfitting.
- *Performance Evaluation:* The very last gadget accomplished extraordinarily nicely: fMRI accuracy: 98.9%, MRI accuracy: 98.6%, EEG accuracy: 98.8%. These results show that the use of a combination of brain test statistics with deep learning models can be a totally effective and correct manner to hit upon dyslexia.

V. Discussion

The research reviewed highlight that system mastering and deep getting to know techniques are each effective for identifying dyslexia, but the techniques fluctuate primarily based at the language being studied. in the case of Hindi, the Devanagari script provides precise challenges that require cautious characteristic choice. commonplace troubles like out of place vowel symbols, wrong syllable placement, and mistakes with joined characters make traditional fashions along with SVM and Random woodland greater suitable for figuring out those styles [45].

On the other hand, models built for English benefit from access to large image datasets and rely more on deep learning techniques that are good at recognizing visual patterns. The work by way of Alkhurayyif and Sait (2023) [46] added a realistic and lightweight model the usage of MobileNetV2 and SSD Lite. This method reached ninety nine.2% accuracy by means of detecting not unusual handwriting problems such as letter reversals and uneven spacing. it's miles particularly useful in real-life settings like classrooms or cell gadgets due to its fast and green design. any other method based on brain imaging [47] used fMRI, MRI, and EEG statistics to educate fashions like EfficientNet B7 and Bi-LSTM. these performed high accuracy, near 99%, but the use of clinical scans makes it harder to apply this device outside medical environments.

Altogether, these studies represent three levels of dyslexia detection: traditional fashions that paintings well for languages like Hindi, real-time deep mastering fashions for English handwriting, and complicated brain-test-primarily based methods used in studies and healthcare. future work ought to study the way to connect language-based features with scalable deep mastering fashions, make use of greater numerous statistics, and consciousness on building systems which might be clean to apply and apprehend in colleges and clinical settings.

VI. Limitations And Future Work

Despite the fact that Smith et al. (2020) [1] and Venkatesh et al. (2021) [13] brought the maximum correct consequences for English and Hindi dyslexia detection, every examine had its own set of obstacles.

- English version (Smith et al., 2020): Effective in detecting letter formation errors however not adaptable to non-Latin scripts.
- Hindi Model (Venkatesh et al., 2021): Performed well for akshar-primarily based detection but required larger and extra numerous datasets for generalization.

In contrast to other research, a key challenge in multilingual studies—which include the ones through Singh & Williams (2017) and Das & Chen (2017)—was the constrained range in their datasets. Their models tended to paintings higher whilst trained and examined on a unmarried language. This shows the importance of making AI systems that can handle more than one languages and adapt to unique scripts successfully.

VII. Conclusion

From the contrast of different studies, the work through Smith et al. (2020) will be the most accurate approach for detecting dyslexia in English, at the same time as the technique with the aid of Venkatesh et al. (2021) proves to be the only for identifying dyslexia in Hindi script. those findings show that language-particular models perform higher while they're designed to handle the specific functions of every script. searching in advance, destiny studies have to goal to construct models which can paintings throughout exceptional languages and scripts through using extra numerous and multilingual datasets.

As part of our destiny paintings, we plan to apply large datasets that encompass specific Hindi handwriting samples at the akshar degree and longer English writing passages. this could help us improve the accuracy of dyslexia detection in both languages. We also intend to enhance our deep learning models through including script-specific modifications and higher text segmentation techniques to make the fashions more dependable. additionally, we are hoping to use explainable AI to create a bendy device that can be used for dyslexia detection across distinct languages, at the same time as also being smooth for instructors and healthcare professionals to understand and use.

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