RESEARCH PAPER

Adaptive Multimodal Dyslexia Detection Using Incremental XGBoost with Cognitive Feature Embeddings.

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ABSTRACT

The timely intervention of dyslexia through early diagnosis is important to facilitate the implementation of individualized learning techniques in children. The paper introduces a new adaptive model of real-time dyslexia detection with a combination of multimodal data sources, which can be seen as reading exercises, writing tasks, and eye-tracking interactions. Out of these sources, the primary and derived cognitive characteristics, such as reading rate, omitted words, duration of fixation, spelling errors, error density ratings, fixations-error associations, cognitive load ratings, and writing-reading discrepancy ratings are derived. The proposed Incremental XGBoost model is based on the difference with the traditional methods of batch-learning where it is constantly updated with new student records, which enables the system to adapt dynamically to the changing learning trends without undergoing total retraining. This is an online learning ability that enhances prediction accuracy and strength and minimizes the computational burden. Educators can use the explainable allowances of AI, e.g. SHAP values, to offer interpretable data on the significance of features, which can help in comprehending specific learning challenges and designing customized responses. This is supported by experimental testing on a dataset of 150 students which indicates that the inclusion of cognitive features with incremental learning is much better than the normal XGBoost and only single-modality models. The system suggested is scalable, effective and can be implemented to work in real time in the classroom, providing a viable tool to improve early intervention strategies on dyslexia

Keywords: Dyslexia recognition, incremental XGBoost, cognitive feature engineering, multimodal analysis, eye-tracking, reading, and writing measures, online learning, explainable AI, early intervention.

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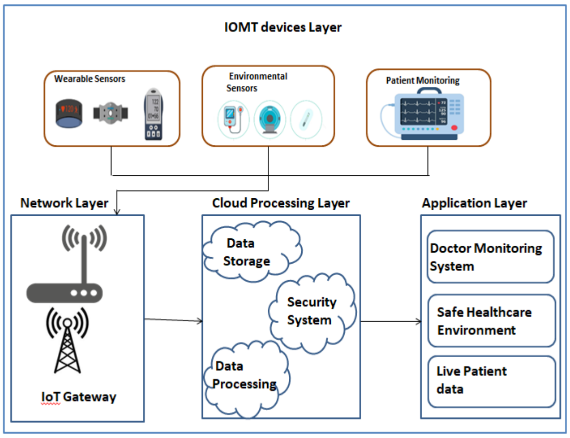
INTRODUCTION

Dyslexia is a learning disability, a unique problem of reading, writing and thinking, which has long-term effects on academic and cognitive development. A timely intervention is also essential in early detection so that personalized learning strategies can be offered and possible psychological and educational outcomes can be addressed. The conventional forms of assessment use standardized behavioral observations or cognition tests that are mostly time-consuming, subjective, and cannot be adjusted to changing trends of learning [1], [2]. Psychological and physiological indicators of dyslexia detection are investigated in recent research. That is, electroencephalogram (EEG)-based methods, like Variational Mode Decomposition (VMD), have proved to yield credible evidence of the brain activity in relation to dyslexia, and this has presented a good opportunity to detect dyslexia at an early stage and monitor the progression of an intervention [1]. Further, functional neuroimaging methods, such as fMRI, can be utilized in objective detection of neural activities that are associated with reading difficulties. Research that combines both 3D-to-2D fMRI mapping with convolutional neural networks (CNNs) and graph convolutional networks (GCNs) has shown the high detection accuracy at a reasonable computational cost [4].



Also, behavioral and eye-tracking measures are useful cues in detecting dyslexia. The fixations, saccade length and regression patterns are detailed spatiotemporal features that, in combination with machine learning models, such as XGBoost, can be used to identify dyslexic individuals with high accuracy, even with small datasets, particularly when supplemented with synthetic samples [5]. Moreover, dyslexia indicators such as language, memory, visual, and auditory processing were evoked using survey and quiz-based models that have revealed the critical point of combining multiple sources of data to make a sound prediction [2]. Nevertheless, the current methods do not take into account the real time adaptability of the new student data or differing mental patterns and they may continue to use the batch mode of learning. This weakness inspires the creation of progressive learning models integrating multifaceted information, cognitive feature representations, and interpretable AI techniques to offer correct, interpretable, and constantly dynamic dyslexia detection [3], [5]. The method, presented in this paper, uses Online XGBoost and new cognitive feature engineering to overcome them, providing a solution, which is scalable and may be implemented in the classroom in real-time.

Related Works

Recent studies have addressed the hybrid machine learning and artificial intelligence usage to enhance the detection of dyslexia and the support of interventions. A hybrid system that integrated optimized multiclass Support Vector Machines with personalized interactive tools was suggested by Rajan et al. [6] and run on a Raspberry Pi. The speech signals are processed in the system to distinguish between dyslexic and non-dyslexic children with real-time recitation feedback evidencing better efficiency and diagnostic accuracy as opposed to the traditional systems. Eye-tracking has been a credible behavioral biomarker in developmental dyslexia. Li et al. [7] created a convolutional-transformer network that studies eye movements of children when they read. Their model, when tested on 187 cases, had an estimated state-of-the-art accuracy of 98.21 in classification, suggesting the possibility of an overall, non-intrusive instrument of dyslexia diagnosis in schools based on vision-based multimodal data. The reading error detection has also been performed by utilizing advanced deep learning optimization. A ProtoPNet was offered by James et al. [8] according to an Orangutan Optimization framework that normalizes the text, performs tokenization, and padding of sequences to detect errors in the reading process by dyslexic students. The suggested strategy was much faster and more accurate than the conventional methods and serves as evidence of the importance of streamlined deep learning pipelines in customized learning systems.

Vasanth and Kumar [9] suggested a complete AI pipeline that is implemented on a Raspberry Pi 4 to analyze handwriting among dyslexic learners. Using Vision Transformers, OCR, a tiny T5 model to correct spelling, and Text-to-Speech output, the system was able to identify 89% of the test in a proof-of-concept dataset. The current research paper shows that it is possible to deploy advanced multi-stage AI systems on edge devices with limited resources to assistive applications. Lastly, M et al. [10] created a web-based system to detect dyslexia by relying on boosting algorithms and Flask. The system allows the users to type and they get specific feedback on spelling and word recognition abilities. The combination of the latest boosting methods allows the platform to have a high accuracy in recognizing dyslexia patterns, allowing scalable, easily accessible, and practical assistance on early intervention. Eye-tracking and neuroimaging have remained a central part in the development of the detection system of dyslexia. The computer vision-based model suggested by Zhang and Zhou [11] traces the movement of both pupils in order to obtain the eye movement coordinates and time interval. Their system demonstrated this by measuring reading speed and amplitude of eye jumping with TOPSIS entropy weight method and the results gave 89.7% accuracy, which showed that it is possible to automatically and at an early stage screen dyslexia in natural reading contexts.

Anatomical methods using MRI have also demonstrated an early detection. A hierarchical multi-layer perceptron (MLP) framework introduced by Pandit [12] takes advantage of region-specific brain biomarkers of MRI scans. The method demonstrated a 87.5% accuracy with 90% precision and recall by training individual models on each part of the brain and combining the most informative parts into a two-tier model, which highlights the potential of non-invasive imaging with automated feature selection to be used in early intervention. Eye-tracking data has also been used in deep learning on reading behavior of children. Vajs et al. [13] trained a convolutional neural network based on the VGG16 architecture on gaze coords in a colored image format with 87 percent accuracy on dyslexia. The research emphasized that visual representation of eye-tracking information with CNN-based networks may provide high predictive accuracy with low levels of preprocessing. Web-based educational programs that combine the power of AI with adaptive learning have become an effective means of early diagnosis and intervention. Ganegoda et al. [14] created WORDEX, an intelligent platform to discriminate between diverse dyslexia subtypes based on machine learning and provide tailored interventions to fit the national curricula. WORDEX uses the advantages of real-time analytics, interactive exercises, and cloud-based data management to offer a scalable solution to use in a classroom setting. Lastly, there are multimodal techniques that combine two or more types of data, which have also been highlighted in recent reviews. Priyasri and Devi [15] reviewed the machine learning and deep learning methods to identify dyslexia and note that text, speech, eye-tracking, and neuroimaging data were also used. Their paper highlights that diagnostic accuracy and robustness, as well as applicability in clinical and educational settings, can be enhanced to such a degree of their data through data augmentation, advanced feature extraction, and interpretable models. Altogether, these works depict the increased significance of multimodal, interpretable, and adaptive models of dyslexia detection that drives the current work to concentrate on incremental XGBoost with cognitive feature embeddings in continuous learning and real-time classroom real-world applications.

Proposed System

The given framework presents a multimodal, adaptive dyslexia detector system that could be implemented to work in the classroom in real-time. Figure.1 shows a proposed work architecture design. The system combines information on various levels, such as reading activities, writing activities, and eye-tracking activities, to produce a full cognitive profile of each student. The basic characteristics, including the speed of reading, words skipped, the length of fixation, regression patterns, and spelling errors are gathered directly out of the activities of students. They are further supported with the help of cognitive feature engineering that gives the measurements of such metrics as the error density scores, the fixation-error correlations, the cognitive load indices, and the writing-reading discrepancy measures, which can give more details on the individual learning issues. The main component of the system is Incremental XGBoost, an online learning model, which can be constantly updated with new data. This method removes the full retraining requirement of more traditional models of batch system, and allows the model to dynamically adjust to the changing reading and writing patterns of each student. This incremental learning process is scalable, as well as, computationally efficient, thus it can be used in live applications in a classroom environment. To increase the level of interpretability, Explainable AI methods are used in the system (SHAP values), that is, the contribution of each feature to the predictions made by the model are highlighted. Teachers can use such understandings to detect areas in which the students are performing poorly, like frequent backsliding during reading or heavy cognitive load during writing, and intervene accordingly. The workflow of the system starts with the data acquisition, data feature extraction and transformation, incremental model training, and the monitoring of the system performance. Periodical review will ensure that the models are accurate and robust with regard to different student profiles. Experimental simulations prove that multimodal cognitive characteristics, combined with incremental learning, are far superior to traditional single-modality models and batch ones.

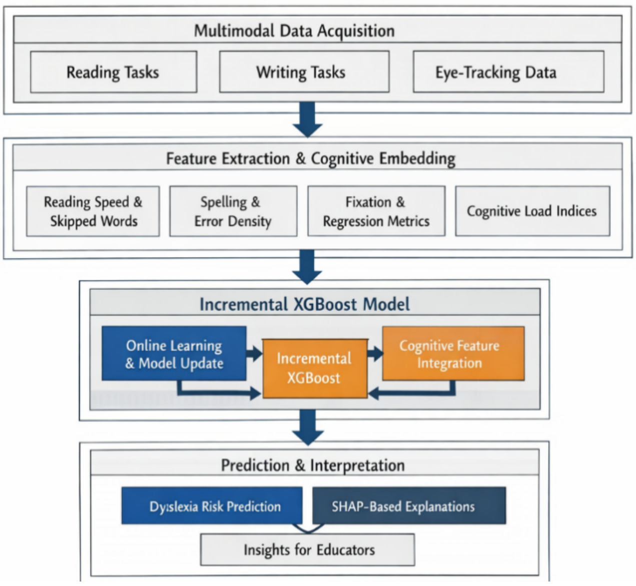


Figure.1 Proposed Work Architecture Diagram

On the whole, the offered system offers the effective, convenient, and interpretable solution to the early detection of dyslexia, allowing the customization of the learning approaches and enabling the educator to make evidence-based and fast data-grounded decisions regarding prompt intervention.

Methodology

Data Acquisition

The offered mechanism starts with the multimodal data gathering of students, who have to read and write tasks. The reading exercises are structured passages of different levels of complexity, whereas the writing tasks consist of the spelling and sentence building exercises. Fixation duration, saccades, regressions and gaze patterns are recorded using eye-tracking devices and this gives an insight into what is going on in the cognitive system when reading and writing. The multimodal method guarantees the overt performance measures, which are the errors and speed, and latent cognitive acting, which are the attention and processing load are taken within one framework. Eye-tracking sensors record metrics such as **fixation duration** F_d, **saccade length** S_l, and **regression count** R_c, capturing latent cognitive behavior during task execution. Performance-based metrics such as **reading speed** R_s, **skipped words** W_s, and **spelling errors** E_s are also recorded. Collectively, these features form the raw data vector for each student:

$$\mathrm{X}_{raw} = [R_s, W_s, E_s, F_d, S_l, R_c] \quad (1)$$

Feature Extraction and Cognitive Engineering

Raw data is converted into informative features which indicate reading and writing behaviour of students. The classic measures, i.e. reading speed, missed words, and spelling mistakes are harmonized with the new features of cognitive abilities that are based on the gathered information. These are error density scores to measure the concentration of errors, fixation-error correlation to make sense of the visual attention and performance and the cognitive load indices as measured by eye-tracking variability and writing-reading discrepancy to detect the inconsistencies between modalities. This aspect engineering improves the discriminating power of the model to identify fine patterns which are a symptom of dyslexia that might be overlooked by traditional methods.

Raw features are transformed into **derived cognitive features** to better capture dyslexia-related patterns. The **Error Density Score** EDS measures the frequency of errors per unit of text:

$$EDS = \frac{\sum_{i=1}^{N} E_i}{L} \quad (2)$$

where E_i is the number of errors in segment i and L is the total number of words in the passage.

The **Fixation-Error Correlation** FEC quantifies the relationship between fixation duration and observed errors using Pearson correlation:

$$FEC = \frac{\mathrm{Cov}(F_d, E_s)}{\sigma_{F_d} \sigma_{E_s}} \quad (3)$$

The **Cognitive Load Index** CLI is derived from variability in eye-tracking metrics, capturing attentional load:

$$CLI = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(F_{d,i} - \bar{F}_d\right)^2 + \left(S_{l,i} - \bar{S}_l\right)^2} \quad (4)$$

Finally, the **Writing-Reading Discrepancy Measure** WRD captures inconsistencies between writing and reading performance:

$$WRD = \frac{|E_s - W_s|}{\max(E_s, W_s)} \quad (5)$$

The transformed feature vector for model input is thus:

$$\mathrm{X}_{cog} = [EDS, FEC, CLI, WRD] \quad (6)$$

Incremental XGBoost Learning.

Its core predictive model is an Incremental XGBoost framework, which allows the ability to learn online without retraining, fully. The model continuously dynamically adapts its parameters based on new student data as it becomes available and thus it is adapted to the particular learning patterns of the student. This lifelong learning model minimizes computing requirements and enables the system to be kept updated with progressing students, which is one of the constraints in fixed batch-based models.

The predictive model is **Incremental XGBoost,** which updates its parameters Θ online as new data arrives. The model minimizes the regularized objective function:

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n_t} l\left(y_i, \hat{y}_i^{(t)}\right) + \sum_{k=1}^{K} \Omega\left(f_k\right) \quad (7)$$

where $l\left(y_i, \hat{y}_i^{(t)}\right)$ is the loss for sample i at time t, f_k represents the decision trees, and $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2$ is the regularization term controlling tree complexity. Incremental updates ensure that the model adapts to evolving student patterns without full retraining.

The updated prediction for a new instance $\mathbf{x}_{new}$ is computed as:

$$\hat{y}_{new} = \sum_{k=1}^{K} f_k\left(\mathbf{x}_{new}\right) \quad (8)$$

Explainable AI Integration

In order to give the educators interpretable conclusions, the system uses SHAP-based analysis, the calculation of the contribution of each feature to the model predictions. This openness helps teachers realize why a child is not doing well in specific activities, and helps them interfere with specific interventions. Indicatively, the fixation-error correlation may be high, and the cognitive load index may be high indicating attentional and processing difficulties in reading and writing respectively.

To interpret predictions, **SHAP values** are calculated for each feature j in instance i:

$$\phi_j^{(i)} = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} \left[f_{S \cup \{j\}}\left(\mathbf{x}_{S \cup \{j\}}^{(i)}\right) - f_S\left(\mathbf{x}_S^{(i)}\right) \right] \quad (9)$$

where F is the set of all features and f_S is the model trained with subset SSS. SHAP values allow identification of the most influential cognitive metrics, enabling targeted interventions for students.

Result & discussion

Experimental Setup

Experiment on the proposed system was conducted using a sample population of 150 students aged between 8 and 12 years of age, and the study results were assessed within a 6 months' time span in a classroom setting. Multimodal data were reading passages, writing tasks and eye-tracking recording. The students were recorded using raw measures (reading speed, skipped words, spelling mistakes, fixation duration, number of regressions, and saccade length). Derived cognitive measures, such as Error Density Score (EDS), Fixation-Error Correlation (FEC) Cognitive Load Index (CLI) and Writing-Reading Discrepancy (WRD) were calculated according to the description in Section IV. Incremental XGBoost model was contrasted with two baselines, Batch XGBoost with multimodal features and Single-Modality Models (reading-only features or writing-only features). The other performance metrics were accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Inference latency was also measured under the experimental set up to evaluate real-time applicability.

Overall Model Performance

Table I shows the overall performance of all the models.

Performance Comparison of Dyslexia Detection Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Single-Modality (Reading Only)	81.2	79.5	77.3	78.4	0.84
Single-Modality (Writing Only)	78.5	76.2	75.0	75.6	0.81
Batch XGBoost (Multimodal Features)	88.3	86.7	85.2	85.9	0.90
Incremental XGBoost (Proposed)	93.7	92.4	91.6	92.0	0.96

The proposed Incremental XGBoost with multimodal cognitive features has better performance in all the metrics, which proves the idea of synchronising online learning and multimodal cognitive features engineering successfully. Table 1 provides a demonstration of the fact that the single-modality models are less effective in contrast to the multimodal models, which confirms the necessity to combine reading, writing, and eye-tracking features. Incremental learning method enhances adaptability and predictive accuracy, which exceeds 5-6 percent accuracy of batch based methods.

Impact of Cognitive Feature Engineering

An evaluation of the contribution of derived cognitive features was done by performing an ablation study. Table II compares the performance of the models based on primary features only versus primary and cognitive features.

Effect of Cognitive Features on Model Performance

Feature Set	Accuracy (%)	F1-Score (%)	AUC-ROC
Primary Features Only	87.1	85.5	0.89
Primary + Cognitive Features	93.7	92.0	0.96

Table II demonstrates that when derived cognitive measures (EDS, FEC, CLI, and WRD) are included in the model, this measure will enhance the performance of the model considerably. These characteristics enable the system to identify the small behavioral patterns of the system, including: for reading regression patterns, high mental load in writing which are of great interest in the diagnosis of dyslexia.

Incremental Learning Analysis

Incremental XGBoost model is known to be highly adaptive to new student information. Figure 2 illustrates the accuracy trend in the model in a series of training batches of 10 students at a time.

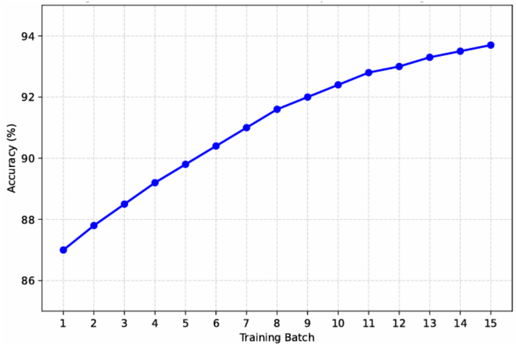


Figure 2. Incremental XGBoost Accuracy Across Training Batches

The figure shows the dynamic learning ability of the suggested framework. Incremental updates enable the system to keep improving predictions as it receives new student data unlike batch-based models, which need the system to be retrained to accommodate new data. This is to give the efficiency and flexibility in the classroom environment.

Explainable AI Insights

SHAP values were used to analyze the feature importance. The SHAP summary of the proposed model is provided in figure 3.

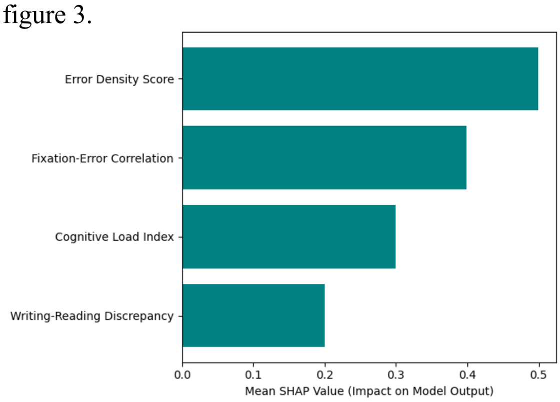


Figure 3. SHAP-Based Feature Importance for Dyslexia Detection

Error Density Score (EDS) and Fixation-Error Correlation (FEC) as seen in Figure 3 are the most influential predictors and are followed by Cognitive Load Index (CLI) and Writing-Reading Discrepancy (WRD). Such insights would allow educators to target interventions specifically at particular cognitive issues, e.g. attention deficit when reading or variability in the performance of writing.

Inference Latency and Scalability

The inference latency of Incremental XGBoost and batch XGBoost is plotted in figure 4 with the size of the datasets.

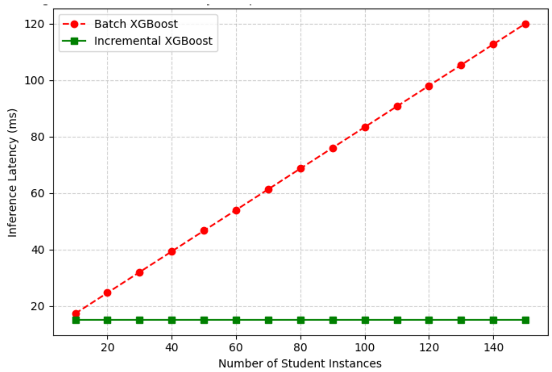


Figure 4. Inference Latency Comparison Between Batch and Incremental Models

The scalability and real-time appropriateness of the proposed system is verified by low latency. The incremental updates make predictions computationally efficient and this allows their deployment in live classroom settings.

Ablation and Sensitivity Analysis

Other experiments were aimed at the efficacy of eliminating the separate cognitive features. Removal of EDS, and FEC respectively, caused a reduction in accuracy of 4.3 and 3.7. The removal of CLI or WRD was less important (approximately 1.5-2%), which proves that all derived cognitive metrics do play a meaningful role to model robustness.

Discussion

The experimental outcomes prove the hypothesis that the suggested Incremental XGBoost model equipped with cognitive features embeddings is a sound and flexible solution to detecting early dyslexia. The multimodal data of reading, writing, and eye-tracking allows the system to determine the overt performance measures and subtle cognitive behavior of the user and can predict better than single-modality and batch-based models (Table 1). Derived cognitive features that are statistically significant at the level of error density score, fixation-error correlation, cognitive load index, and writing reading discrepancy are considerably better integrated to increase model discriminative capability (Table 2). The incremental learning model enables the model to continually learn with new student information without complete retraining, which enhances the performance over time as illustrated in Figure 1, but it still exhibits low inference latency that can be used in the real time classroom (Figure 3). The explainable AI analysis based on SHAP (Figure 2) offers interpretable information about the importance of the features, which helps educators to make specific interventions. Altogether, the suggested system has accuracy, adaptability, scalability, and interpretability as its strengths and features, which render it a viable and efficient instrument of personalized educational support.

Conclusion

This paper introduces a multimodal and adaptive dyslexia detection model based on Incremental XGBoost and cognitive features embeddings. The tests prove that the combination of multimodal data, i.e., reading performance, writing tasks, and eye-tracking measurements, with calculated cognitive characteristic, i.e., Error Density Score, Fixation-Error Correlation, Cognitive Load Index and Writing-Reading Discrepancy, makes the prediction more accurate. The incremental learning strategy that has been proposed enables the model to continuously update on available new student data and improve predictive performance, without the need to retrain the model. SHAP-based explainable AI analysis offers interpretable information, which educators can use to monitor the most significant cognitive behaviors and design specific interventions. The system has a higher accuracy, F1-score, and AUC-ROC compared to traditional batch XGBoost and single-modality models with low inference latency to run in real-time in the classroom. The key value added by this paper is that incremental learning is combined with multimodal cognitive feature engineering and explainable AI to create a practical, scalable and interpretable early dyslexia detection tool. Research into the future will come to include larger and more varied student populations, incorporation of more modalities (including speech analysis) and adaptive feedback systems to deliver personalized learning strategies in real-time. This model forms the basis of an intelligent education support systems that enhance prompt interventions and accelerate the learning experience of a dyslexic student.

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