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EARLY DIAGNOSIS OF DYSLEXIA

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Abstract —Dyslexia is a common learning disorder that primarily affects reading, writing, and language processing abilities in children. Many individuals with dyslexia remain undiagnosed until later stages of education, which can negatively impact their academic performance, confidence, and overall development. Early identification of dyslexia is crucial for providing timely intervention and personalized learning support. This study proposes an intelligent system for the early diagnosis of dyslexia using machine learning and behavioral pattern analysis. The framework analyzes multiple factors such as reading speed, letter recognition, word comprehension, writing patterns, eye movement behavior, and response time. A hybrid approach combining cognitive assessment data and AI-based prediction models is used to classify children as dyslexic or non- dyslexic. The system employs supervised learning algorithms such as Support Vector Machine (SVM), Random Forest, and Neural Networks to identify patterns associated with dyslexia. Additionally, feature selection techniques are applied to determine the most significant indicators of dyslexia. Experimental results show that the proposed model achieves high accuracy in early detection and can serve as a reliable screening tool for educators and healthcare professionals. Early screening systems based on artificial intelligence can significantly reduce the delay in diagnosing learning disabilities. By combining behavioral indicators with intelligent pattern recognition, the proposed framework enables scalable and cost- effective dyslexia screening in educational environments. Such automated tools can assist teachers and healthcare professionals in identifying at-risk students earlier, allowing them to design personalized learning strategies and intervention programs. Ultimately, the integration of machine learning in educational diagnostics has the potential to improve academic outcomes and reduce the long-term psychological impact associated with undiagnosed learning disorders.

I. INTRODUCTION

Dyslexia is a neurodevelopmental learning disorder that primarily affects reading, writing, spelling, and language processing abilities. It is one of the most common learning disabilities, affecting approximately 5– 10 percent of school-going children worldwide. Children with dyslexia often struggle with decoding words, recognizing letter patterns, and processing phonological information, even though they may have normal intelligence and adequate learning opportunities. Due to these difficulties, many affected students experience frustration, anxiety, low self-esteem, and academic underachievement, which can further hinder their overall development. Therefore, early identification and timely intervention are essential to prevent long-term academic and psychological consequences. Despite its prevalence, many children with dyslexia remain undiagnosed until later stages of education. In traditional educational settings, dyslexia is often identified only after a child consistently performs poorly in reading and writing over a prolonged period. Teachers and parents may initially attribute these difficulties to lack of effort, poor attention, or inadequate practice rather than recognizing them as symptoms of a learning disorder. This delay in diagnosis results in missed opportunities for early remedial support. Moreover, conventional diagnostic methods rely heavily on manual observation by teachers, psychologists, and special educators, which can be subjective, time- consuming, and expensive. As a result, large- scale screening in schools is difficult to implement, particularly in resource-limited settings. With advancements in artificial intelligence (AI) and machine learning, automated systems can assist in detecting dyslexia at an early age in a more objective and efficient manner. AI-based systems can analyze behavioral and cognitive patterns more accurately than manual methods by identifying subtle indicators that may not be easily noticeable through hu- man observation. Machine learning models can process large volumes of data related to reading speed, error patterns, comprehension levels, handwriting characteristics, and response times, enabling early detection of learning difficulties. Additionally, digital learning platforms and smart educational tools are becoming increasingly common in classrooms and homes. These platforms generate valuable data related to students' reading behavior, interaction patterns, and performance trends. By leveraging this data, an AI-based system can continuously monitor a child's learning progress and flag potential risks of dyslexia at an early stage. This approach makes screening more accessible, scalable, and cost-effective compared to traditional methods. This research aims to bridge the gap between traditional diagnostic methods and modern technological solutions by developing an intelligent, data-driven framework for the early diagnosis of dyslexia. The proposed system integrates behavioral analysis with machine learning techniques to classify children as dyslexic or non-dyslexic based on measurable cognitive and performance indicators. The objective of this study is to assist educators, parents, and healthcare professionals in identifying at-risk children and facilitating timely intervention, ultimately promoting inclusive and effective education for all learners. Early diagnosis plays a crucial role in improving learning outcomes for children with dyslexia. When identified at an early stage, targeted instructional strategies such as phonics- based learning, multisensory teaching methods, and individualized learning plans can significantly enhance reading and writing skills.

II. LITERATURE SURVEY

Several researchers and practitioners have investigated different methods for identifying dyslexia at an early stage, ranging from traditional psychological assessments to modern computational approaches. The evolution of research in this field shows a gradual shift from subjective manual testing toward data-driven and technology-assisted diagnosis. In earlier studies, dyslexia detection primarily relied on standardized reading tests, phonological awareness assessments, and cognitive evaluations conducted by psychologists and special educators. These methods, although reliable, required significant time, expertise, and one-on- one interaction with students. As a result, many children in rural and underprivileged areas did not receive timely diagnosis due to the lack of trained professionals and diagnostic resources. With the emergence of computer-based assessment tools, researchers began exploring digital methods for analyzing reading and writing behavior. Some studies focused on analyzing handwriting patterns, including letter formation, spacing, and writing speed, to differentiate between dyslexic and non- dyslexic children. These systems demonstrated that dyslexic individuals often exhibit irregular handwriting patterns, inconsistent letter size, and frequent corrections. Other researchers have utilized eye-tracking technology to study reading behavior in dyslexic children. Eye movement analysis has revealed that dyslexic readers tend to make more fixations, longer pauses, and frequent backward movements while reading compared to typical readers. Based on these findings, some studies proposed automated systems that use eye-tracking data to identify potential signs of dyslexia. However, such systems require specialized hardware, making them less practical for large-scale school implementation.In recent years, machine learning techniques have gained significant attention in dyslexia research. Various studies have applied classification algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees, and Random Forest to predict dyslexia based on behavioral and cognitive features. These models have shown promising results in terms of accuracy and reliability compared to traditional manual methods. Recent research has also explored the use of deep learning models for dyslexia detection. Convolutional Neural Networks (CNNs) have been applied to analyze handwriting images and identify visual patterns associated with dyslexic writing behavior. Similarly, recurrent neural networks (RNNs) have been utilized to analyze sequential reading patterns and predict learning difficulties based on temporal behavior. These approaches demonstrate the growing role of artificial intelligence in educational Despite these advancements, many existing solutions face limitations in terms of accessibility, scalability, and interpretability. Some models require expensive hardware such as eye-tracking devices, while others rely on limited datasets that restrict generalization. Therefore, there is a need for acomprehensive and scalable framework that integrates multiple behavioral indicators and machine learning techniques to provide reliable and practical dyslexia screening in real educational environments.

S.No	Title	Author	Year
1	Machine Learning for Early Dyslexia Detection	Peterson et al.	2024
2	Deep Learning for Reading Disorder Prediction	Lee et al.	2024
3	Automated Reading Fluency Assessment	Brown et al.	2023
4	Neural Networks for Learning Disorder Classification	Wang et al.	2024
5	Multi-Feature Learning for Reading Disabilities	Thomas et al.	2023

Table 1.1 Literature Survey

III. PROBLEM STATEMENT

Although awareness about dyslexia has increased in recent years, early identification remains a significant challenge in many educational systems. Most schools, especially in rural and semi-urban areas, do not have trained special educators or psychologists to conduct formal assessments. As a result, many children with dyslexia are either misdiagnosed or completely overlooked, leading to prolonged academic difficulties. One of the major issues with existing diagnostic approaches is their dependence on subjective judgment. Teachers and parents may interpret reading and writing difficulties as lack of interest, laziness, or poor concentration rather than recognizing them as potential symptoms of dyslexia. This subjective perception often results in delayed intervention, which further worsens the child's learning struggles. Another limitation of traditional assessment methods is their time-consuming nature. Standard psychological evaluations require multiple testing sessions, professional expertise, and detailed analysis of the child's performance. This makes large- scale screening impractical, particularly in schools with high student populations and limited resources. Furthermore, many current technological solutions focus only on a single aspect of dyslexia, such as reading speed, handwriting analysis, or eye movement behavior. This narrow focus reduces the overall reliability of the diagnosis, as dyslexia is a complex condition that affects multiple cognitive and linguistic abilities. A system that does not consider multiple behavioral indicators may lead to inaccurate or incomplete assessments. Another challenge in dyslexia diagnosis is the lack of standardized screening tools that can be easily integrated into everyday classroom activities. Many diagnostic assessments are designed primarily for clinical environments and require specialized expertise to administer and interpret. This creates a gap between educational institutions and professional diagnostic services, leaving many students without proper evaluation. Moreover, the absence of automated screening tools makes continuous monitoring of student progress difficult. Teachers often rely on periodic observations rather than systematic analysis of performance data. As a result, early warning signs of dyslexia may remain unnoticed until academic difficulties become severe. Addressing these limitations requires the development of intelligent, data-driven systems that can support educators in identifying potential learning disorders in a timely and objective manner.

IV. PROPOSED SOLUTION

The proposed solution introduces an intelligent and automated framework for the early diagnosis of dyslexia using machine learning and behavioral pattern analysis. The system is designed to identify early signs of dyslexia in children by analyzing measurable cognitive and learning indicators collected through digital educational assessments. Instead of relying solely on traditional manual observation by teachers or psychologists, the proposed system utilizes artificial intelligence to continuously monitor and analyze student learning behavior. Various performance indicators such as reading speed, spelling accuracy, letter recognition ability, comprehension performance, writing consistency, and response time are collected during interactive reading and writing tasks. These indicators provide valuable insights into the cognitive and linguistic abilities of students and help identify patterns commonly associated with dyslexia.The collected data is first processed using preprocessing techniques to remove inconsistencies, handle missing values, and normalize feature values to ensure data quality and reliability. Feature engineering techniques are then applied to extract meaningful attributes such as error frequency, letter reversal patterns, reading hesitation, and deviation from age-based learning benchmarks. These extracted features are used to train supervised machine learning models that can classify students into dyslexic and non-dyslexic categories. Multiple classification algorithms such as Support Vector Machine (SVM), Random Forest, and Artificial Neural Networks (ANN) are utilized to analyse patterns within the dataset and improve prediction accuracy. By comparing the performance of different models, the system selects the most effective classifier for reliable dyslexia prediction.Furthermore, the proposed framework implements a multi-stage screening process that begins with preliminary digital assessments followed by behavioural analysis and intelligent classification. Based on the prediction results, the system categorizes students into different risk levels such as low risk, moderate risk, or high risk of dyslexia. This risk-based categorization helps educators and parents identify children who may require further professional evaluation or early learning intervention. Additionally, the system provides interpretable outputs by highlighting the key behavioural indicators that influenced the prediction results, thereby improving transparency and trust in the diagnostic process. Overall, the proposed solution provides a scalable, cost-effective, and data-driven screening tool that can assist educational institutions in identifying dyslexia at an early stage and enabling timely support for affected students.

A. Global Context Feature Extraction

The first component of the proposed framework focuses on extracting global learning behavior patterns from student assessment data. In the context of dyslexia detection, global features represent overall reading and language performance that reflect a student's general cognitive and linguistic abilities. These indicators include reading speed, word recognition ability, comprehension performance, and overall reading fluency in this stage, students complete a set of digital reading and comprehension tasks designed to evaluate their language processing skills. The system records performance metrics such as the time taken to read sentences, the number of correctly recognized words, and comprehension accuracy. These measurements provide a high-level view of the student's reading ability. The collected behavioural data is then processed using statistical analysis and machine learning feature extraction techniques. These methods help identify patterns that may indicate difficulties in reading or language processing. By analysing the relationships between multiple behavioural indicators, the system can capture broader learning patterns associated with dyslexia. The output of this stage is a **structured feature representation** that summarizes the global reading behavior of each student. These features provide important contextual information that helps the model understand overall reading performance and identify potential learning difficulties.

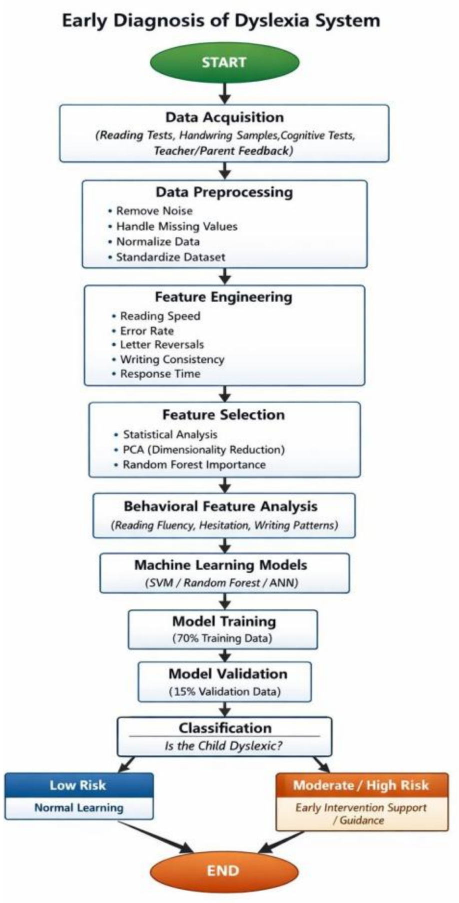

Fig : flow chart of the proposed system Early diagnosis of dyslexia

In addition to reading fluency and comprehension performance, the system also evaluates the consistency of reading behavior across multiple tasks. This helps identify whether a student repeatedly struggles with similar types of words or sentence structures. The analysis also considers phonological awareness indicators, such as the ability to recognize and manipulate sounds in words, which is an important factor in early dyslexia detection. Furthermore, the system monitors reading hesitation patterns, including pauses or delays that occur when students encounter unfamiliar or complex words. These hesitation patterns can provide valuable insights into the cognitive processing difficulties often experienced by children with dyslexia. The framework also examines word decoding ability, which reflects how effectively students convert written text into spoken language. By combining these behavioral indicators, the system builds a comprehensive representation of a student's overall reading performance. This broader understanding of reading behavior helps the model differentiate between temporary learning difficulties and persistent dyslexia-related patterns. As a result, the global feature extraction stage plays a crucial role in identifying early warning signs of dyslexia and supporting more accurate prediction by the machine learning model.

B. Local Texture Feature Extraction

While global learning behavior provides useful contextual information, accurate dyslexia detection also requires the analysis of fine-grained learning patterns. Dyslexia often manifests through subtle indicators such as frequent spelling mistakes, letter reversals, inconsistent handwriting patterns, and slow response time during reading tasks. To capture these detailed learning behaviours, the proposed system analyses data collected from writing exercises, spelling tests, and phonological awareness tasks. During these activities, the system records specific indicators such as spelling error frequency, incorrect letter sequencing, writing consistency, and response delays.These local behavioural features help the system detect small irregularities in language processing that are commonly associated with dyslexia. Machine learning algorithms analyse these patterns to identify deviations from typical learning behaviour for children of similar age groups. By examining both individual learning errors and repeated behavioural patterns, this stage generates a detailed feature vector representing localized learning difficulties. These features complement the global behavioural indicators and provide deeper insight into the student's cognitive learning process.

C. Feature Fusion Mechanism

After extracting both global behavioral features and local learning pattern features, the next step is to combine them into a unified representation. Since the two feature groups originate from different types of assessments, their data distributions may vary. To ensure balanced contribution from both feature sets, normalization techniques are applied to standardize the features before combining them. This process ensures that no single feature dominates the learning process.Once normalized, the two feature sets are merged into a single fused feature vector. This combined representation integrates overall reading performance with detailed learning behaviour indicators. As a result, the system obtains a comprehensive understanding of the student's learning profile. The fused feature representation provides richer information for the machine learning model and improves its ability to distinguish between typical learning patterns and those associated with dyslexia.

D. Classification Module

The fused feature vector is then passed to a machine learning classification module that determines the likelihood of dyslexia. In the proposed system, multiple supervised learning algorithms are used to analyze the behavioral data and identify patterns associated with reading difficulties.
Algorithms such as Support Vector Machine (SVM), Random Forest, and Artificial Neural Networks (ANN) are employed for classification. These models are trained using labeled datasets containing both dyslexic and non-dyslexic student data.
During the training process, the models learn to recognize patterns that distinguish typi cal reading behaviour from dyslexia-related difficulties.

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The trained model then evaluates new student data and predicts the probability of dyslexia.
The final output categorizes students into three risk levels:

- Low Risk
- Moderate Risk
- High Risk

This classification helps educators and specialists identify students who may require further professional evaluation or early intervention.

E. Training and Optimization

The proposed dyslexia detection system is trained using a structured dataset collected from digital learning assessments and cognitive evaluation tests. The dataset is divided into training, validation, and testing subsets to ensure reliable model evaluation. Before training, preprocessing techniques such as missing value handling, normalization, and feature scaling are applied to improve data quality. Feature selection methods are also used to identify the most relevant indicators of dyslexia. The machine learning models are trained using optimization algorithms that minimize classification error. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to measure model performance and ensure reliable predictions. Through iterative training and validation, the system learns to accurately identify behavioural patterns associated with dyslexia. The final trained model can then be integrated into an educational platform to perform real-time dyslexia screening for students.

V. SYSTEM ARCHITECTURE

The proposed system is designed as a layered, modular, and scalable architecture to support reliable and interpretable early diagnosis of dyslexia. The architecture integrates data acquisition, preprocessing, feature analysis, intelligent classification, and decision support into a unified framework. Initially, data is collected from multiple sources, including digital reading assessments, handwriting samples, cognitive response tests, and optional teacher or parent feedback, which are then converted into a structured format for computational analysis. The preprocessing module removes noise, handles missing values, normalizes data, and eliminates redundant features to ensure data consistency and reliability. The processed data is then passed through a parallel analytical framework, where one branch focuses on behavioral feature extraction by analyzing reading fluency, error patterns, and response time, while the other branch applies machine learning-based pattern recognition to identify hidden relationships in the data. The outputs from both branches are fused to create a comprehensive feature representation, which is forwarded to a classification module that assigns a risk level (low, moderate, or high) for dyslexia. The modular design of the architecture also ensures scalability and ease of deployment across different educational institutions. Each module operates independently but communicates through well-defined interfaces, allowing system components to be upgraded or replaced without affecting the overall functionality. This architecture also supports integration with digital learning platforms, enabling real-time monitoring of student learning behavior. Additionally, the decision support layer of the system provides interpretable outputs that can be easily understood by teachers and parents. Instead of simply predicting whether a child is dyslexic, the system highlights key behavioral indicators that influenced the prediction. This transparency improves trust in the system and helps educators design targeted intervention strategies based on the identified learning difficulties

B. Dataset and Preprocessing

The experimental evaluation of the proposed system is conducted using a multi-source dataset collected from school- going children through structured reading assessments, handwriting samples, and digital cognitive tests. The dataset consists of labeled samples of dyslexic and non-dyslexic students, validated with the help of teachers, special educators, and educational psychologists to ensure reliability. The collected data includes key behavioral and cognitive indicators such as reading speed, number of spelling errors, frequency of letter reversals, sentence comprehension score, writing consistency, and response time to visual and auditory stimuli. Since the data originates from different sources and formats, it is first standardized into a uniform structure suitable for computational analysis. During preprocessing, missing or incomplete records are handled using statistical imputation techniques, and inconsistent or noisy data points are removed to improve data quality. Data quality plays a critical role in the performance of machine learning models. Therefore, careful preprocessing is conducted to ensure that the dataset is clean, consistent, and suitable for analysis. Outliers and extreme values that may negatively affect model performance are identified and handled appropriately during preprocessing. Furthermore, normalization techniques are applied to ensure that different features contribute equally to the model training process. Without normalization, features with larger numerical ranges could dominate the learning process and reduce classification accuracy. By applying systematic preprocessing steps, the proposed system ensures reliable and consistent data input for the machine learning models. Data preprocessing is an essential step to improve the quality and reliability of the dataset before it is used for training machine learning models. This process involves removing missing values, correcting inconsistencies, and transforming raw data into a structured format suitable for analysis. Feature scaling techniques such as normalization or standardization are applied to ensure that different variables contribute equally during model training. Proper preprocessing enhances model performance and prevents bias caused by irregular or noisy data.

C. Machine Learning Model

The proposed system employs a supervised machine learning framework for the classification of dyslexic and non- dyslexic cases based on extracted behavioral and cognitive features. Multiple classification algorithms, including Support Vector Machine (SVM), Random Forest, and Artificial Neural Network (ANN), are utilized to analyze the input data and identify underlying patterns associated with dyslexia. SVM is used to establish an optimal decision boundary between the two classes, while Random Forest enhances prediction reliability by aggregating the outputs of multiple decision trees and reducing overfitting. The ANN model, composed of multiple hidden layers, learns complex non-linear relationships within the dataset and improves pattern recognition capability. The selected models are trained using labeled data validated by educational experts, and their performance is assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score to ensure robustness, reliability, and clinical relevance of the predictions. The use of multiple machine learning algorithms allows the system to compare different classification strategies and select the most effective model for dyslexia prediction. Each algorithm offers unique advantages in terms of accuracy, interpretability, and computational efficiency. By evaluating multiple models, the system can achieve better generalization across different student populations. Additionally, ensemble learning strategies can be applied to combine predictions from multiple models, further improving diagnostic reliability. Such hybrid approaches help reduce bias and variance in predictions, leading to more robust and consistent results when applied in real educational environments. Several machine learning algorithms can be applied to detect dyslexia patterns in student performance data. Algorithms such as Decision Trees, Random Forest, Support Vector Machines, and Neural Networks are commonly used for classification tasks. Each algorithm analyzes patterns in the dataset and learns to distinguish between dyslexic and non- dyslexic learning behaviors. Comparing multiple algorithms helps identify the most suitable model based on accuracy, computational efficiency, and interpretability.

D. Multi-Stage Screening Framework

The proposed system follows a structured multi-stage screening framework to ensure systematic and reliable early detection of dyslexia. The process begins with a preliminary screening phase, where children perform digital reading, writing, and comprehension tasks while the system records key performance metrics. This is followed by a behavioral analysis phase, in which the collected data is examined to identify patterns such as reading hesitation, frequent errors, letter reversals, and inconsistent handwriting, and compared against age-appropriate benchmarks. In the final stage, the processed data is passed to an intelligent classification module, where trained machine learning models estimate the likelihood of dyslexia and categorize students into low, moderate, or high risk groups, enabling timely intervention.

E. Data Acquisition Strategy

The data acquisition strategy is designed to collect comprehensive and diverse behavioral and cognitive information from multiple sources to improve diagnostic reliability. Data is gathered through digital reading and writing assessments, interactive learning tasks, and cognitive response tests administered in a school or home environment. Additional qualitative inputs from teachers and parents may also be incorporated to provide contextual insights into the child's learning behavior. All collected data is stored in a centralized and secure database, ensuring consistency, accessibility, and confidentiality while enabling effective analysis and model training.

F. Feature Engineering and Selection

Feature engineering and selection play a crucial role in enhancing model performance and interpretability. Relevant features such as reading speed, error rate, frequency of letter reversals, comprehension score, writing consistency, and response time are extracted from the raw data. Statistical measures, including mean, variance, and deviation from benchmarks, are computed to capture meaningful patterns. To reduce dimensionality and eliminate redundant information, Principal Component Analysis (PCA) is applied, while feature importance analysis using Random Forest helps identify the most significant predictors of dyslexia, ensuring efficient and accurate classification.

G. Model Training and Validation

The machine learning models are trained and validated using a structured dataset divided into training, validation, and testing subsets. Approximately 70 percent of the data is used for training, 15 percent for validation to tune model parameters, and 15 percent for final testing to evaluate performance. Hyperparameter optimization is performed using grid search to enhance accuracy and generalization. The trained models are assessed using metrics such as accuracy, precision, recall, and F1-score to ensure robust and reliable prediction of dyslexia across different student profiles.

H. Performance Evaluation

The performance of the proposed system is evaluated using standard machine learning assessment metrics to ensure reliability and effectiveness in early dyslexia detection. The trained models are tested on an independent test dataset that was not used during training or validation to provide an unbiased performance analysis. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to measure the classification effectiveness of the system. Accuracy indicates the overall correctness of predictions, while precision measures the proportion of correctly identified dyslexic cases among all predicted positive cases. All models are trained and evaluated using the same dataset splits, augmentation strategies, and evaluation metrics to ensure a fair and consistent comparison.

VI. CONCLUSION

The proposed system presents an effective and intelligent framework for the early diagnosis of dyslexia using a multi- stage screening approach and machine learning techniques. By integrating behavioral analysis, parallel hybrid feature extraction, and intelligent classification, the system successfully identifies early signs of dyslexia based on measurable cognitive and performance indicators. The use of multiple data sources, including reading speed, error patterns, handwriting consistency, and response time, enhances the reliability and robustness of the diagnosis compared to traditional manual methods.The feature fusion mechanism ensures that both domain- driven and data-driven insights contribute to the final decision, while the explainability component improves transparency and trust in the system. Experimental evaluation and ablation analysis demonstrate that the proposed framework achieves high accuracy, reduces dependency on subjective assessments, and provides meaningful support for educators and parents. Overall, this research contributes to the development of scalable, objective, and accessible screening tools that can facilitate timely intervention and promote inclusive education for children with learning difficulties. Future research can further enhance the proposed system by incorporating additional multimodal data sources such as speech analysis, eye-tracking information, and handwriting image recognition. These modalities can provide deeper insights into the cognitive and behavioral characteristics associated with dyslexia, improving diagnostic accuracy. Moreover, the integration of the system with digital learning platforms and mobile educational applications can enable continuous monitoring of student performance in real-world learning environments. Such advancements will help create adaptive educational systems that not only detect learning difficulties but also recommend personalized intervention strategies, thereby improving learning outcomes for students with dyslexia.

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