Multimodal AI Framework for Early Detection of Dyslexia in Children

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Dyslexia is a lifelong learning disorder. It is associated with how the brain functions, making it difficult for children to read, write, and retain information. If it is not identified when a child is young, then it can make it very challenging for the child to perform well at school. It can also negatively affect the child's self-esteem. Therefore, it is very important to identify the problem during early childhood. This is even more critical in a country such as Pakistan, where awareness of dyslexia is limited and early screening facilities for children are not widely available. Usually, Traditional methods used to determine whether children have dyslexia, the process is slow, may produce inaccurate conclusions, and often examines only a single aspect of the disorder. To address these limitations, this document proposes an approach in which multiple features are integrated into a computer-based system to identify dyslexia. The program analyzes handwriting patterns and cognitive processing characteristics. When evaluated using data from data 200 children, the program achieved 96.9% accuracy and 91.7% sensitivity in determining whether a child has dyslexia. It successfully identified all cases, including the small number of children diagnosed with dyslexia, while only five children without dyslexia were incorrectly classified. Although this study has certain limitations, including a relatively small dataset and related constraints, the findings indicate that this multimodal behavioral and perceptual analysis approach improves the identification of children with dyslexia. The proposed approach offers a practical solution for early screening in educational settings, with potential for further improvement through additional data modalities.

Keywords: Dyslexia, Early Detection, Handwriting Analysis, Cognitive Assessment, Multimodal System, Machine Learning, Educational Screening.

Introduction:

Dyslexia is a learning difficulty that impairs a child's ability to read, write, and process information, even when the child is otherwise intelligent and receives good instruction. If dyslexia is not identified early, it can lead to long-term learning difficulties and reduce the child's self-confidence. Therefore, early and accurate identification is essential so that the child can receive appropriate support and effective learning strategies. Most current studies identify dyslexia using only a single type of information, such as handwriting images, speech, or cognitive assessments. Individually, these approaches do not capture both the behavioral and cognitive aspects of children [1][2][3][4][5][6][7]. When computational methods have been applied to predict dyslexia using handwriting data, audio data, eye-tracking records, and memory assessments, these approaches perform better than traditional methods [8][9][10][11][12][13][14][15][16]. However, relying on only one modality can still lead to incorrect predictions. To address this limitation, the present study proposes an integrated approach that combines handwriting analysis and cognitive testing to detect dyslexia at an early stage. Data were collected from approximately 200 students and analyzed using Support Vector Machine (SVM), Random Forest (RF), InceptionV3, and VGG16 models. the most effective were the VGG16 model and the cognitive assessment module, achieving 96.88% accuracy; while SVM and RF achieved 83.33% and 91.67%, respectively. These results indicate that integrating behavioral data and cognitive assessments provides a more robust approach for identifying dyslexia than using a single modality. The proposed approach offers a reliable and practical method for early detection, which can support teachers in providing targeted educational assistance to students.

Literature Review and Related Work and Research Gap:

Dyslexia is a neurodevelopmental disorder that can impair reading, writing, spelling, and information processing, even in individuals with normal cognitive abilities. Early detection is critical to reduce repeated learning difficulties and associated cognitive challenges. Recent advances in artificial intelligence have shown promise in enhancing dyslexia detection. Computational models have been successfully applied to handwriting analysis, memory assessment, and, in ongoing research, speech analysis and eye-tracking evaluations.

Handwriting-based Dyslexia Detection:

Handwriting analysis, employing convolutional neural networks (CNNs) and transfer learning architectures such as VGG16 and InceptionV3, has shown high effectiveness in identifying early signs of dyslexia [17] Additionally, brain-based memory signals, analyzed using classifiers such as Support Vector Machine (SVM) and Random Forest, enhance detection capabilities [17]. However, challenges remain in understanding the applied methodologies, and the use of large or low-cost data acquisition devices presents limitations [18][3][12].

Memory-based Dyslexia Detection:

Working memory and cognitive deficits are closely associated with dyslexia. Research indicates that classifiers like SVM and Random Forest can successfully identify dyslexic patterns using memory-based features. Nevertheless, the limited size or isolated nature of many datasets restricts the generalizability of these findings. By utilizing publicly available datasets, our memory module achieved strong classification performance, highlighting the importance of cognitive features in early dyslexia detection.

Multimodal Approaches:

Only a few studies incorporate multiple modalities, including handwriting, memory, speech, and eye-tracking data. Some research suggests that multimodal approaches improve detection accuracy and provide a more comprehensive assessment; however, integrating data from multiple sources remains challenging. The present work addresses this challenge by combining handwriting and memory features into a single functional system.

Most AI-based dyslexia studies focus on single modalities, which do not capture the full cognitive and motor complexity of the disorder. Handwriting studies often rely on limited datasets with minimal comparison between machine learning and deep learning models, whereas memory-based studies use small datasets and lack optimized decision strategies. Few practical systems integrate both handwriting and memory within a unified AI framework. This study addresses these gaps by combining handwriting and memory features, evaluating multiple models, and applying optimized strategies for early and reliable dyslexia detection.

Material and Method:

This study presents a multimodal AI framework for the early detection of children with dyslexia by integrating handwriting analysis with memory-based cognitive assessment. Various machine learning and deep learning algorithms are employed to accurately classify children as dyslexic or non-dyslexic, providing a scalable platform for future multimodal data integration.

The proposed framework aims to enhance detection accuracy by capturing both behavioral and cognitive characteristics associated with dyslexia. It also allows flexibility for incorporating additional data modalities in future implementations. This approach facilitates early screening and timely educational intervention for affected children, ultimately supporting educators and clinicians in making more informed decisions.

As illustrated in **Figure 3**, the system integrates handwriting and memory modules for dyslexia detection.

Handwriting Module:

Data Collection:

Handwriting samples were collected from approximately 200 students from schools and tutoring centers. Students were instructed to write specific sentences to ensure consistency across samples. The dataset contains images of handwriting from both children with and without dyslexia, representing diverse styles, letter formations, and word structures. Examples of handwriting from both groups are presented in Figures 1 and 2.

Sample of Handwritten Data: (Dyslexic Child):

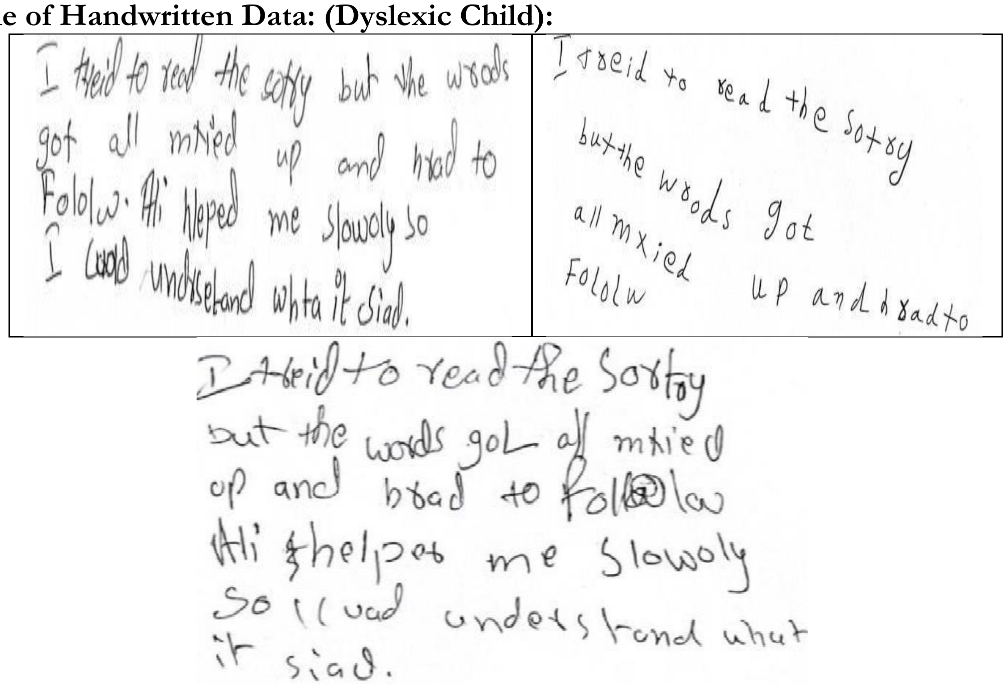


Figure 1 (a,b,c). Samples of handwritten data from a dyslexic child

Sample of Handwritten Data: (Non- dyslexic Child):

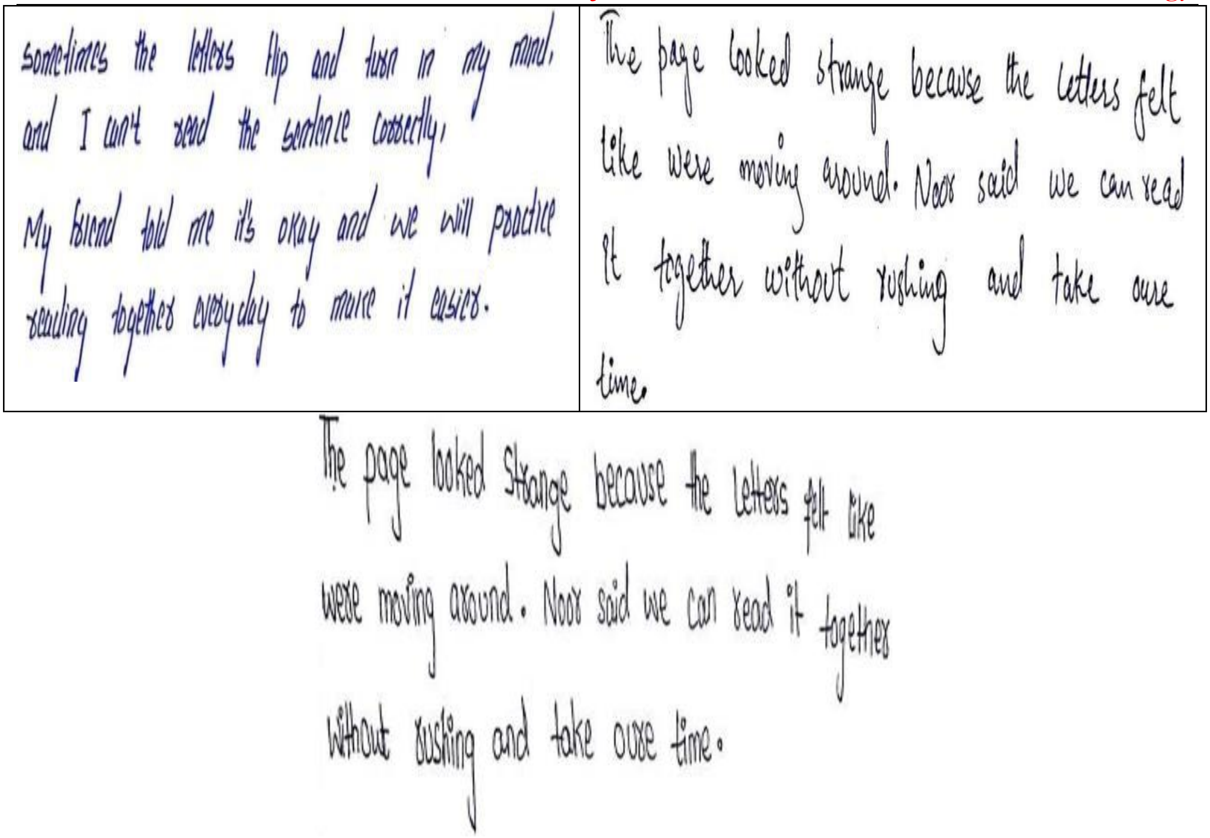


Figure 2 (a,b,c). Samples of handwritten data (Non-dyslexic child)

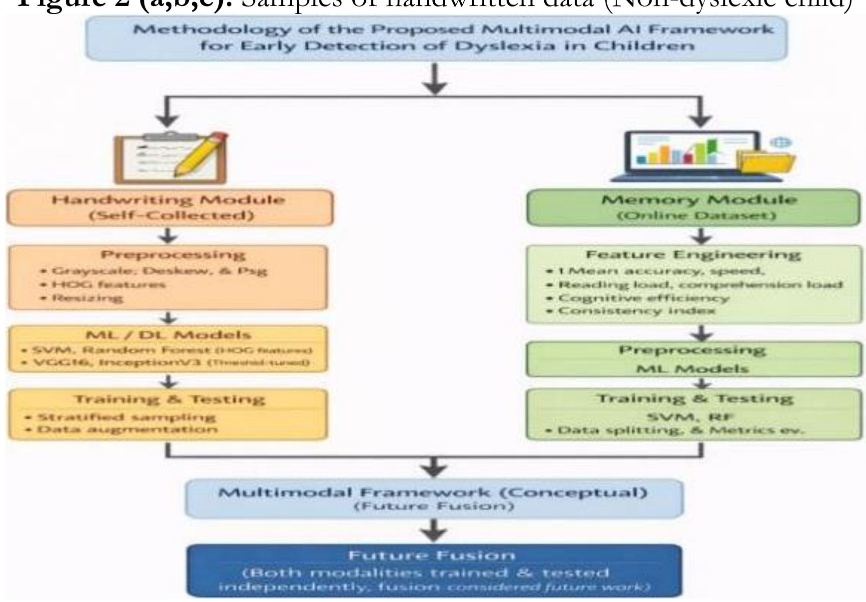


Figure 3. Methodology of proposed multimodal AI framework for early Detection of dyslexia in children.

Preprocessing:

All handwriting images were converted to grayscale, deskewed to correct text orientation, and enhanced using histogram equalization to improve contrast. Images were resized to 128×128 pixels for CNN-based models and 224×224 pixels for VGG16 and InceptionV3. For traditional machine learning models, Histogram of Oriented Gradients (HOG) features were extracted to represent structural characteristics of handwriting.

Models:

Support Vector Machine (SVM) was trained on HOG features using a radial basis function (RBF) kernel to model non-linear handwriting patterns, providing strong generalization for binary classification. Random Forest (RF) was employed as an ensemble classifier using multiple decision trees trained on random feature subsets, reducing overfitting and enhancing robustness.

VGG16, a pre-trained deep convolutional neural network, was fine-tuned to extract hierarchical handwriting features, enabling effective discrimination of subtle stroke and shape variations.

InceptionV3 was used to capture multi-scale handwriting features through parallel convolutional filters, with threshold tuning applied to improve classification performance.

Training and Testing:

The handwriting dataset was split into training and testing sets using stratified sampling to maintain class balance. Data augmentation techniques, including rotation, zooming, shifting, and contrast adjustment, were applied to enhance model robustness. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrices.

Memory Module:

Data Collection:

Memory and cognitive assessment data were obtained from publicly available online datasets involving children. The dataset includes measures related to task accuracy, processing speed, reading load, and comprehension ability.

Feature Engineering:

Features were computed to capture memory and cognitive patterns as follows:

acc_mean and **acc_std**: Mean and variability of task accuracy.

speed_mean: Average task completion speed.

reading_load and **comprehension_load**: Combined cognitive effort.

cognitive_efficiency = acc_mean / speed_mean.

consistency_index = acc_mean / acc_std.

Preprocessing:

Numerical features were standardized using a Standard Scaler, categorical features were one-hot encoded, and missing values were imputed using appropriate statistical methods. Class imbalance was addressed through oversampling of the minority class.

Models:

An SVM with an RBF kernel was used to model non-linear relationships among cognitive features, while Random Forest was employed for robust classification by aggregating multiple decision trees, effectively handling mixed feature types.

Training and Testing:

The memory dataset was split into 60% training set and 40% testing set. Data processing and modeling were performed using integrated pipelines that included preprocessing, features, transformation, and classification steps. The classification threshold was adjusted to optimize the F1-score for dyslexia detection.

Multimodal Framework:

In this study, the handwriting and memory modules were evaluated independently. In future implementations, their outputs can be combined using ensemble methods or decision-level fusion to enhance detection performance. Incorporation of additional modalities, such as speech and eye-tracking, may further improve the system's accuracy and reliability.

Results and Discussion:

Handwriting-Based Dyslexia Detection Module:

The handwriting module was trained on approximately 200 samples and evaluated on a balanced test set consisting of 64 handwritten images (32 non-dyslexic and 32 dyslexic). Four models, SVM, Random Forest, InceptionV3, and VGG16, were analyzed.

Table 1. Performance comparison of handwriting-based models

Model	Test Accuracy
SVM	71.88%
Random Forest	81.25%
InceptionV3 (t=0.70)	90.63%
VGG16	96.88%

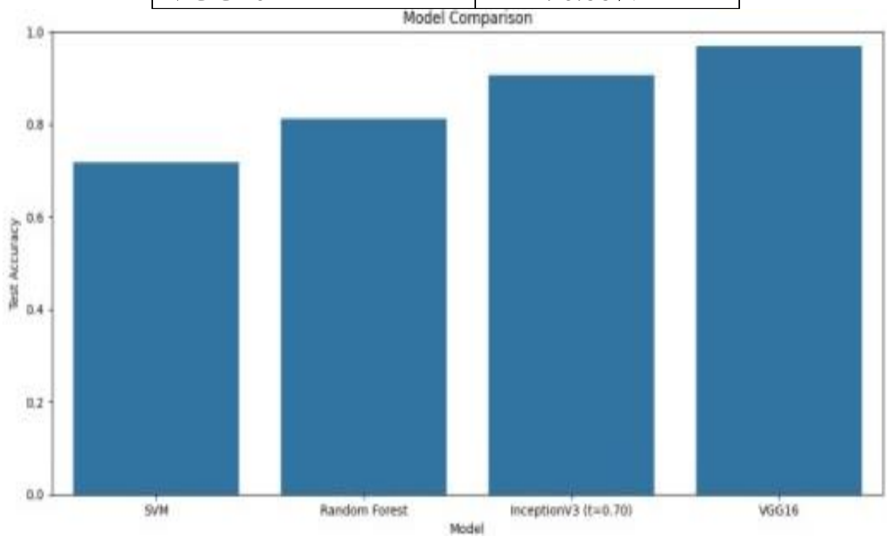


Figure 4. Comparative test accuracy of SVM, Random Forest, InceptionV3 (threshold = 0.70), and VGG16 on the handwriting test.

Figure 4 compares the performance of SVM, Random Forest, InceptionV3 (threshold = 0.70), and VGG16 on the handwriting dataset (Table 1). VGG16 achieved the best results, with the highest precision (96.88%) and overall precision, recall, and F1-score (0.97), showing strong discrimination of dyslexic handwriting. InceptionV3 followed with 90.63% accuracy and balanced class performance. Random Forest outperformed SVM but remained less consistent than deep learning models. Overall, transfer learning-based deep convolutional networks significantly outperform traditional methods in handwriting-based dyslexia detection.

Table 2. Class-wise performance metrics for handwriting models

Model	Class	Precision	Recall	F1-Score	Support
SVM	Normal	0.82	0.56	0.67	32
	Dyslexia	0.67	0.88	0.76	32
	Macro avg	0.74	0.72	0.71	64
Random Forest	Normal	0.92	0.69	0.79	32
	Dyslexia	0.75	0.94	0.83	32
	Macro avg	0.83	0.81	0.81	64
Inception V3 (t=0.70)	Normal	0.86	0.97	0.91	32
	Dyslexia	0.96	0.84	0.90	32
	Macro avg	0.91	0.91	0.91	64
VGG16	Normal	1.00	0.94	0.97	32
	Dyslexia	0.94	1.00	0.97	32
	Macro avg	0.97	0.97	0.97	64
SVM	Normal	0.82	0.56	0.67	32

Detailed class-wise metrics are reported in **Table 2**. VGG16 obtained perfect recall (**1.00**) for the Dyslexia class, while InceptionV3 also demonstrated a strong balance between precision and recall. Random Forest showed improved dyslexia recall compared to SVM, whereas SVM exhibited higher misclassification of Normal samples.

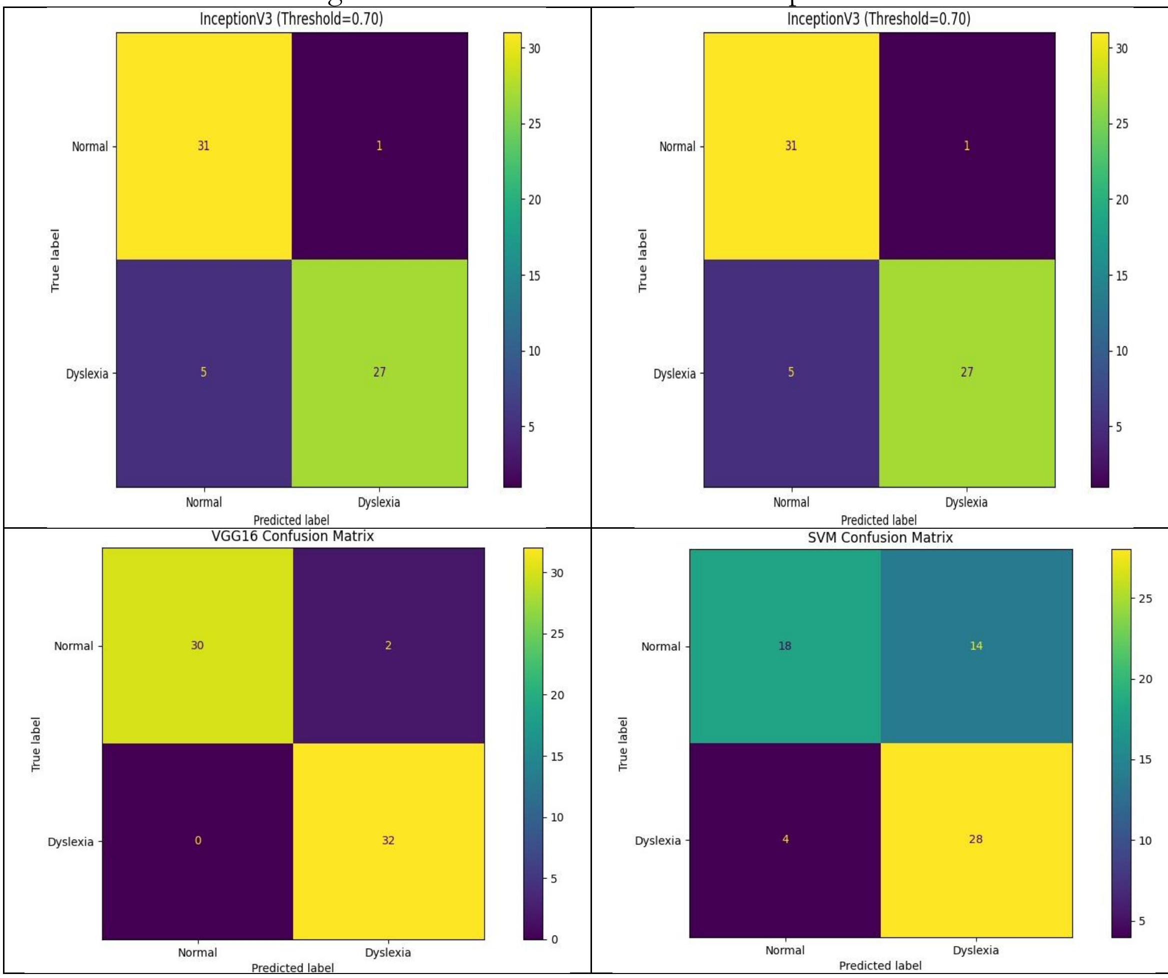
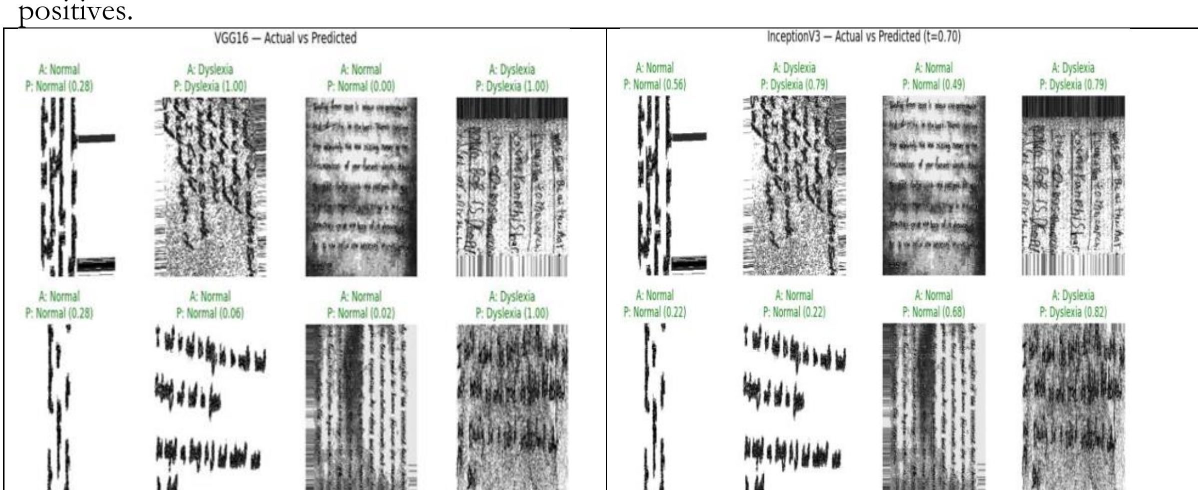


Figure 5. Confusion matrices for (a) InceptionV3 (threshold = 0.70), (b) Random Forest, (c) VGG16, and (d) SVM on the test dataset (n = 64).

The confusion matrices presented in Figure 5(a) provide insight into classification errors across all models. VGG16 achieved zero false negatives, while InceptionV3 and Random Forest showed limited misclassification. SVM produced the highest number of false positives.



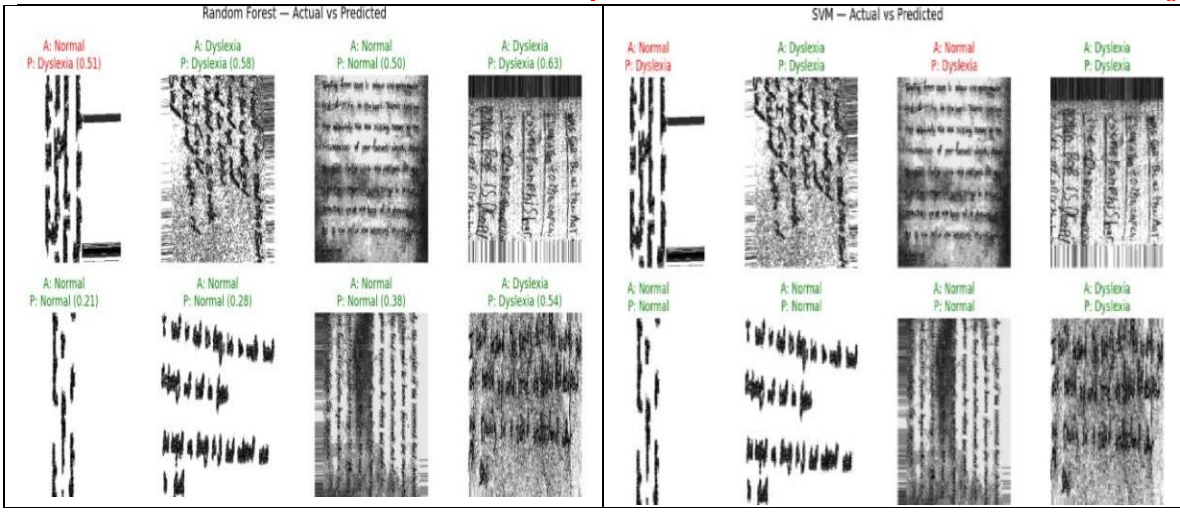


Figure 6. Qualitative examples of actual vs. predicted labels with confidence probabilities 6b on selected test samples for (a) VGG16, (b) InceptionV3 (threshold = 0.70), (c) SVM (incorrect predictions highlighted in red), and (d) Random Forest.

Qualitative prediction examples are shown in Figure 6(a–d). Deep learning models assigned higher confidence to correct predictions and successfully captured dyslexic handwriting characteristics such as irregular spacing, misalignment, and distorted letter shapes.

Memory-Based Dyslexia Detection:

The memory module was evaluated on 12 test samples (6 Control and 6 Dyslexia) using SVM and Random Forest with optimized thresholds.

Table 3. Accuracy comparison of memory-based models

Model	Test Accuracy
SVM (threshold=0.127)	83.33%
Random Forest threshold = (0.296)	91.67%

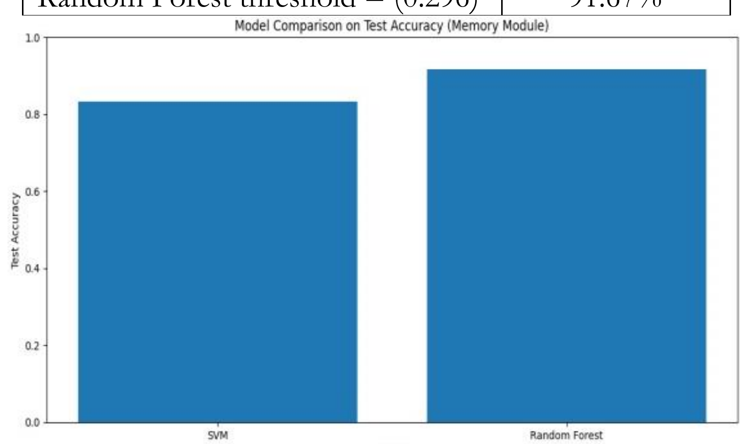


Figure 7. Comparative test accuracy of SVM and Random Forest on the memory module test set.

Table 3 reports test accuracy, where Random Forest outperformed SVM (91.67% vs. 83.33%). The accuracy comparison is illustrated in Figure 7.

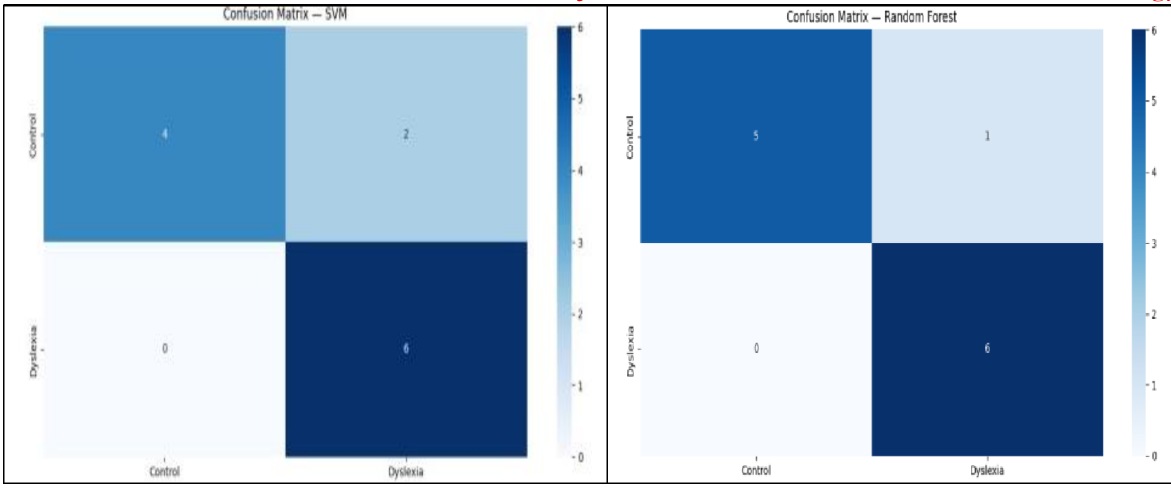


Figure 8. Confusion matrices for (a) SVM and (b) Random Forest on the memory module test dataset (n = 12)

Figure 8 presents the confusion matrices. SVM correctly identified all dyslexia cases but misclassified two control samples, resulting in perfect sensitivity but lower specificity. Random Forest also detected all dyslexia cases while misclassifying only one control sample, demonstrating higher overall accuracy and better discrimination.

Table 4. Class-wise performance metrics for memory models

Model	Class	Precision	Recall	F1-Score	Support
SVM (threshold=0.127)	Control	1.00	0.67	0.80	6
	Dyslexia	0.75	1.00	0.86	6
	Macro avg	0.88	0.83	0.83	12
Random Forest (threshold=0.296)	Control	1.00	0.83	0.91	6
	Dyslexia	0.86	1.00	0.92	6
	Macro avg	0.93	0.92	0.92	12

Performance metrics for each class are in Table 4. Both models had perfect recall (1.00) for Dyslexia, so no cases were missed. Random Forest had more precision and a better balance across classes.

This study presents an experimental multimodal AI-based prototype aimed at supporting early dyslexia detection through combined analyses of handwriting behavior and short-term memory performance. While previous research has primarily focused on detecting dyslexia using only one of these information sources, the proposed system demonstrates how motor and cognitive features can be assessed together within a single framework. Handwriting samples were analyzed using transfer learning–based deep learning models, whereas memory performance was evaluated with ensemble machine learning approaches, providing a non-invasive and automated screening methodology.

Interpretation of Results:

The results indicate that the proposed prototype performs effectively in detecting dyslexia. In handwriting analysis, the VGG16 model achieved the highest accuracy of 96.88% and consistently identified dyslexic samples, demonstrating its ability to capture subtle handwriting patterns associated with dyslexia. InceptionV3 also produced stable and reliable results, supporting the use of deep learning models for handwriting assessment. For the memory analysis module, the Random Forest model achieved an accuracy of 91.67% and successfully detected all dyslexia cases, highlighting its suitability for analyzing cognitive performance differences. High sensitivity in both modules is particularly important for early screening, as missing a dyslexic case can have significant educational and developmental consequences.

Comparison with Existing Studies:

Most prior research in dyslexia detection has focused on single modalities, such as handwriting, eye-tracking, or memory-based tasks, with moderate performance outcomes. In contrast, the present multimodal prototype improves detection performance across both handwriting and memory domains through the use of advanced learning models and self-collected real-world data. This approach provides a more comprehensive understanding of the characteristics of dyslexia than single modality systems.

Contributions and Implications:

The primary contribution of this study is the development of a multimodal AI-based prototype that integrates handwriting and memory features for dyslexia detection. The use of a self-collected handwriting dataset demonstrates the feasibility of acquiring realistic data in varied educational contexts, while the inclusion of memory assessments emphasizes the cognitive dimension of dyslexia. From a practical perspective, this framework can support early screening in educational settings, contributing to international efforts for early diagnosis and intervention for children with developmental reading difficulties. From a research perspective, the findings underscore the importance of multimodal approaches for both understanding and detecting dyslexia.

Limitations:

The current framework remains at a prototype stage and is not yet fully operational. The memory datasets used in this study are limited in size and diversity, which may affect the generalizability of the results. Real-time multimodal integration has not yet been implemented, limiting practical deployment.

Future Work:

Future work will focus on developing a fully operational system capable of instant predictions and automated reporting. Additional data modalities, including speech and eye-tracking, will be incorporated to enhance detection accuracy. Furthermore, data from diverse populations will need to be collected, and real-world testing will need to be necessary before the full potential of the system can be realized.

Conclusion:

This study presents a multimodal AI-based prototype that integrates handwriting analysis and memory assessment for early dyslexia detection. Experimental results demonstrate high accuracy and sensitivity, highlighting the feasibility of automated screening approaches. Although the system is currently limited to a prototype stage, it provides a foundation for future development involving larger datasets, additional modalities, and practical deployment in educational settings.

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