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A Machine Learning Framework for Early Dysgraphia Screening and Support Through Handwriting

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Abstract - Dysgraphia is a learning difficulty that significantly affects handwriting, spelling, and fine motor control, often leading to academic struggles and reduced confidence in children. Early identification is essential, yet current diagnostic practices are time-consuming, costly, and dependent on specialist availability, leaving many cases undetected, especially in under-resourced settings.

This paper proposes a technology-assisted framework for early screening and support of dysgraphia using machine learning–driven handwriting analysis combined with real-time classroom observations. The system leverages mobile-based tools employing techniques such as edge detection and convolutional neural networks (CNNs) to analyse handwriting patterns, while integrating insights from teachers and parents for a holistic evaluation.

Beyond detection, the framework provides actionable, real- time feedback to support educators, families, and clinicians in developing personalized learning strategies, classroom adjustments, and ongoing progress tracking. By making screening accessible, cost- effective, and scalable, the approach reduces reliance on clinical resources and promotes inclusive learning environments. Ultimately, it empowers children with dysgraphia to receive timely interventions, fostering both academic achievement and social confidence from the earliest stages of education.

Keywords— Machine Learning, Artificial Intelligence (AI), Convolutional Neural Network (CNN), Handwriting Analysis, Collaborative Assessment System

1.INTRODUCTION

Early detection and intervention for neurodiverse conditions, particularly dysgraphia, continue to present a considerable challenge for educators, healthcare professionals, and families. Dysgraphia, a learning difficulty primarily associated with handwriting, spelling, and fine motor skills, often leads to reduced academic performance and diminished self-confidence. Many children are not identified until their difficulties have already impacted learning outcomes, making subsequent intervention more complex and less effective.

Timely identification is therefore critical, as it can prevent these struggles from escalating into persistent barriers to learning, social development, and emotional well-being. However, current diagnostic approaches are frequently hindered by their dependence on specialist expertise, which is often limited, costly, and not readily accessible. This issue is particularly pronounced in rural and under- resourced areas, where access to professional evaluation is scarce and delayed, resulting in missed opportunities for early support.

The reliance on traditional diagnostic tools also poses limitations, as these assessments are resource-intensive, time-consuming, and may fail to capture subtle or context-specific variations in handwriting and motor coordination. Consequently, many children remain undiagnosed or are identified only at later stages, by which time the condition may have already contributed to academic underachievement and reduced motivation.

In recent years, research has increasingly emphasized the importance of integrating technology into the process of screening and support. Advances in artificial intelligence (AI), image processing, and data-driven analysis provide promising avenues for developing automated, scalable, and cost-effective tools. Such approaches can reduce reliance on clinical resources while promoting inclusive educational practices. Furthermore, involving multiple stakeholders— including educators, parents, and clinicians—can foster a holistic understanding of the child's challenges and ensure that interventions address academic, social, and emotional needs simultaneously.

Globally, studies have shown that a significant percentage of school-aged children exhibit symptoms of dysgraphia or related handwriting difficulties, yet many remain unidentified until secondary school or later. This delay not only affects their academic progress but also contributes to long-term issues such as reduced participation in classroom activities, withdrawal from written tasks, and heightened anxiety around academic performance. Addressing these challenges at an early stage is essential for ensuring equitable educational opportunities and preventing avoidable disparities in learning outcomes.

Moreover, early screening and intervention for dysgraphia align with broader educational goals of inclusive learning environments. By leveraging AI-driven diagnostic tools and collaborative assessment systems, schools can move beyond reactive approaches to proactive, continuous monitoring of student progress. Such systems have the potential to transform the educational landscape by making learning support more precise, personalized, and accessible. This holistic approach ensures that children with dysgraphia not only overcome handwriting-related barriers but also develop the confidence and skills necessary for long-term academic and personal success.

Therefore, the integration of advanced technologies with collaborative educational practices offers a transformative pathway for early dysgraphia detection. By shifting from delayed, specialist- dependent evaluations to proactive, accessible, and scalable solutions, it becomes possible to foster inclusive learning environments where children receive timely support, enhance their academic performance.

2. LITERATURE SURVAY

Dysgraphia is a learning disorder that creates consistent challenges for children in writing-related activities. Its impact goes beyond difficulties with handwriting, as it also affects fine motor coordination, spelling skills, and fluency in written expression. For many children, everyday academic tasks such as note-taking, completing assignments, or even writing their names become sources of frustration. Over time, these struggles can diminish self-confidence and motivation. Since writing plays a fundamental role in education, early identification is essential, as it allows timely interventions that reduce long-term academic challenges. In recent years, technological advances in artificial intelligence (AI), image processing, and data-driven methods have been widely explored to enhance dysgraphia detection. These approaches aim to make screening faster, more reliable, and accessible, particularly in environments where professional specialists are limited.

Over the past two decades, researchers have explored diverse methods to understand, analyze, and detect dysgraphia, reflecting the growing recognition of its impact on children's academic development. Early studies primarily relied on traditional handwriting analysis techniques, focusing on visual inspection and manual evaluation of written samples. However, the limitations of these methods in terms of subjectivity, time consumption, and scalability led to the adoption of computational approaches. With the rise of artificial intelligence, machine learning, and sensor-based systems, the field has witnessed a shift toward automated, data-driven solutions that not only enhance diagnostic accuracy but also make large-scale screening feasible in classroom and clinical settings.

The reviewed literature can be grouped into two main categories:

1. Analysis Approaches

Gupta et al. [13] introduced a handwriting analysis framework based on contour and edge detection, focusing on low-cost preprocessing techniques that could be applied in large classrooms, though restricted to static features. Lomurno et al. [11] improved geometric handwriting evaluation by combining Procrustes analysis with deep learning, allowing better normalization of shapes and alignment of letters. Bublin et al. [12] developed the *SensoGrip* system, which captured pressure and stroke velocity data from a smart pen to provide dynamic rather than static handwriting features, enhancing robustness. Kunhoth et al. [10] presented a multimodal ensemble method, where handwriting images were processed together with additional features through conditional feature fusion, highlighting the importance of integrating multiple modalities. Nevisi and Tahmasbi [15] introduced a game-based handwriting assessment where hesitation time and error corrections were monitored during gameplay, emphasizing behavioral indicators. Richard and Serrurier [18] applied a machine learning-based feature selection strategy for handwriting patterns, showing that feature optimization significantly improved prediction of both dyslexia and dysgraphia. Similarly, Drotár et al. [19] used classical feature extraction with machine learning to identify which handwriting features were most strongly correlated with dysgraphia risk.

Recent work by Wang et al. [21] incorporated temporal handwriting data by analyzing pen-tip trajectories using recurrent neural networks (RNNs). This approach effectively captured the sequential dependencies between strokes, enabling more fine-grained analysis of fluency and rhythm. Similarly, Martins et al.

[22] introduced graph-based handwriting representations where each character was modeled as a network of connected strokes, allowing deeper structural comparisons between typical and atypical writing patterns. These methods highlight the growing trend of moving beyond static image features to incorporate sequential and relational information.

In addition, Chakraborty and Saha [23] emphasized the role of explainable AI (XAI) in dysgraphia analysis by integrating saliency maps with handwriting classifiers. Their work provided visual feedback on which parts of the handwriting contributed most to classification, making the system more interpretable for teachers and clinicians. This development indicates a shift toward not only accurate but also transparent analysis approaches that support human decision-making. Their work provided visual feedback on which parts of the handwriting contributed most.

2. Detection Approaches

Aparna S. et al. [13] developed a mobile-based handwriting detection application using contour and edge classifiers. While its accuracy was modest, the system demonstrated feasibility for school-level screening. Pratama et al. [11] applied Convolutional Neural Networks (CNNs) to handwriting datasets, achieving more than 80% accuracy and showcasing the effectiveness of CNNs in identifying subtle irregularities. Srivastava et al. [15] expanded on CNN-based methods by combining raw handwriting images with handcrafted features such as pen pressure variations, which resulted in higher detection accuracy than conventional CNNs. Jabbar et al. [14] adopted decision tree classifiers that incorporated handwriting features and behavioral cues, improving classification performance through multi-feature fusion. Palomo-Duarte et al.

[10] developed classroom-integrated detection software that merged teacher feedback with AI predictions, making the system more reliable and usable. Zolna et al. [17] emphasized the importance of dynamic stroke information, showing that it provided superior diagnostic accuracy compared to static handwriting images. Finally, Han [20] reviewed two decades of research on dysgraphia interventions and highlighted the progression from basic diagnostic methods to predictive systems capable of anticipating developmental risks.
More recently, Alonso-Martinez et al. [24] proposed a hybrid detection system that integrated wearable sensors with digital tablets, capturing both neuromotor activity and handwriting strokes simultaneously. This approach significantly improved detection sensitivity in younger children, where handwriting alone may not fully reveal difficulties. Rizvi et al. [25] explored federated learning-based detection, enabling multiple schools to collaboratively train handwriting models without sharing sensitive student data. Their findings suggest that privacy-preserving AI methods can be both practical and effective in large-scale educational settings.

Another line of research, demonstrated by Khan et al. [26], investigated the use of handwriting datasets from multiple languages to build cross- lingual detection models. Their study found that models trained on multilingual data achieved greater generalizability, addressing a key limitation in dysgraphia research where most datasets are language- specific. Likewise, Ortiz and Delgado [27] experimented with attention- based neural networks to focus on critical segments of handwriting, achieving superior classification accuracy by filtering out irrelevant noise.

Conclusion of Literature Survey

Overall, the literature demonstrates a clear transition from traditional handwriting analysis based on static features toward advanced, AI- powered, and multimodal systems. While early methods provided only limited accuracy, the integration of deep learning, multimodal behavioral analysis, and classroom-based applications has significantly improved both diagnostic precision and practical usability. These advancements suggest that intelligent, technology-assisted systems have strong potential for supporting early detection and intervention in dysgraphia.

Beyond accuracy improvements, recent studies emphasize the importance of scalability, inclusivity, and interpretability in dysgraphia detection systems. Cross-lingual and privacy-preserving frameworks broaden accessibility across diverse educational contexts, while explainable AI ensures that teachers and clinicians can trust and understand the outputs of automated tools. The integration of wearable sensors and multimodal data streams further demonstrates that future systems may evolve into holistic platforms capable of capturing both cognitive and motor aspects of writing. Collectively, these advancements suggest that the next generation of dysgraphia detection tools will not only be more precise but also more equitable, transparent, and adaptable to real-world classroom environment.

3.METHODOLOGY

A. OpenCV (Image Preprocessing)

1. Image Capture: The handwritten sample is acquired either through scanning or by taking a photograph in RGB format.
2. Noise Removal: Filters such as Gaussian blur or median filters are applied to remove dust, ruled lines, and smudges, while morphological operations eliminate ink bleed and shadows.
3. Binarization: Thresholding techniques, such as Otsu's or adaptive thresholding, convert the image into a binary form, clearly separating ink strokes from the background.

B. ResNet CNN (Handwriting Pattern Recognition & Dysgraphia Traits)

1. Input: The normalized 224×224 handwriting image is provided as input to the ResNet CNN.
2. Layer-wise Detection: The early layers detect curves and strokes, intermediate layers capture letter shapes, and the deeper layers identify irregular spacing, tremors, or alignment issues.
3. Residual Connections: Skip connections help retain low- level handwriting details, preventing the loss of subtle stroke features during deeper processing.
4. Output Features: The model generates a feature vector that describes the handwriting style, including inconsistencies in size, line stability, and orientation.
5. Classification: The extracted features are finally classified into categories such as "dysgraphia" or "non-dysgraphia."

C. Tesseract OCR (Text Reading & Legibility Analysis)

1. Segmentation: The image is divided into lines, then into words, and finally into characters for recognition.
2. Feature Extraction and Matching: Each character's features are compared against trained character patterns stored in the OCR system.
3. Recognition: The OCR engine predicts the most probable characters, but poor or unclear handwriting reduces recognition accuracy.
4. Word Formation and Correction: Recognized characters are grouped into words, and dictionary-based correction improves accuracy by reducing spelling errors.
5. Confidence Scoring: Each word is assigned a confidence score; consistently low scores and frequent recognition errors suggest reduced legibility.

D. Risk Assessment (Fusion of CNN + OCR)

1. From ResNet CNN: Writing traits such as spacing irregularities, tremors, and inconsistent strokes are extracted for analysis.
2. From Tesseract OCR: Recognition outcomes such as spelling errors, low confidence levels, and letter reversals are evaluated for legibility.

E. Risk Assessment Algorithm

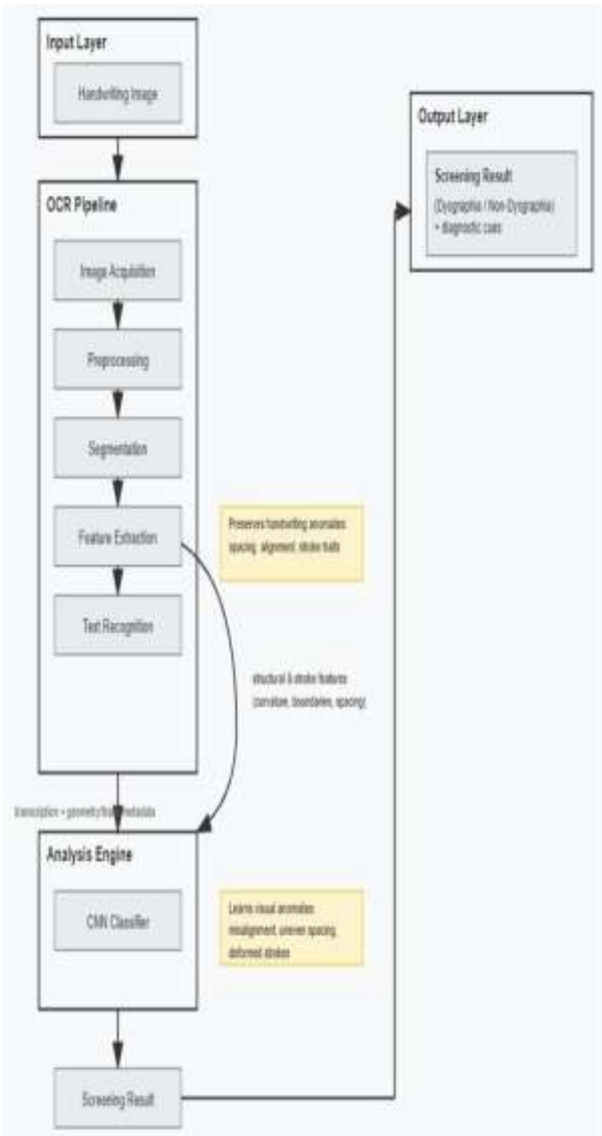
The CNN-based features and OCR-based recognition outcomes are merged using a risk assessment algorithm, which produces a dysgraphia risk score categorized as Low, Moderate, or High.

F. Effect

By combining both handwriting style analysis and legibility evaluation, the system provides a more reliable assessment of dysgraphia, reducing false interpretations and capturing both motor and readability aspects.

While the proposed methodology provides a strong foundation for dysgraphia detection, further improvements can be achieved through the inclusion of multimodal signals beyond static handwriting images. For example, when using smart pens or digital tablets, features such as pen pressure, writing speed, and stroke velocity can be recorded alongside image data. These dynamic signals capture real-time motor control difficulties like inconsistent pressure application, sudden pauses, or repetitive corrections, which often serve as early indicators of dysgraphia. Similarly, eye-tracking technologies can be incorporated to monitor visual attention and letter formation strategies, offering another dimension to understanding how children engage with writing tasks. The integration of such modalities ensures that the system not only detects surface-level handwriting irregularities but also uncovers deeper motor and cognitive processes underlying the disorder.

Fig: Workflow of OCR and CNN



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1. Prediction Process

The prediction begins with a single input, namely a scanned image of handwriting. A Convolutional Neural Network (CNN) is employed to analyze the writing in detail, examining the curves of each letter, the steadiness of the strokes, and the alignment of words. These fine- grained features often distinguish dysgraphia-affected handwriting from normal writing. At the same time, an Optical Character Recognition (OCR) engine attempts to interpret the written content. When the OCR produces a large number of unreadable characters or recognition errors, it indicates that the handwriting is irregular and difficult to process. The outcomes of the CNN's visual analysis and the OCR's recognition accuracy are then combined.The prediction begins with a single input, namely a scanned image of handwriting.

2. Performance Evaluation Metrics

To validate system reliability, predictions are compared with

$$WER = \frac{Insertions + Deletions + Substitutions}{Total\ Words}$$

expert- annotated labels. Several evaluation measures are used. Accuracy represents the proportion of correctly classified samples and is calculated as:

where TP is true positives, TN is true negatives, FP is false positives, and FN is false negatives.

Precision measures the proportion of samples identified as dysgraphia that were actually correct

successfully identified by the model:

The F1 Score provides a harmonic balance

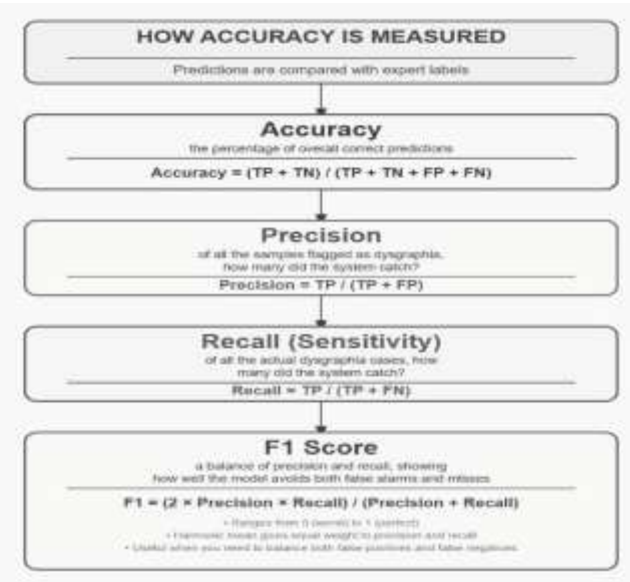

Fig. Accuracy measurement

3. Ensuring Reliability of Results

To strengthen the reliability of results, the model is evaluated using k- fold cross-validation. In this process, the dataset is divided into k equal partitions. The model is trained on k-1 subsets and tested on the remaining one. This process is repeated until every subset has been used as a test set, and the final performance is averaged across all trials. Such a procedure ensures that the system's reported accuracy is not due to overfitting but represents consistent generalization to unseen handwriting samples.

To strengthen the reliability of results, the model is evaluated using *k*-fold cross-validation. In this process, the dataset is divided into *k* equal partitions. The model is trained on *k–1* subsets and tested on the remaining one. This process is repeated until every subset has been used as a test set, and the final performance is averaged across all trials. Such a procedure ensures that the system's reported accuracy is not due to overfitting but represents consistent generalization to unseen handwriting samples.

4. Evaluation of OCR Effectiveness

Since OCR accuracy provides additional insight into handwriting quality, it is measured with two error metrics. The Character Error Rate (CER) is defined as:

$$CER = \frac{Insertions + Deletions + Substitutions}{Total\ Characters}$$

Similarly, the Word Error Rate (WER) is calculated as:

High CER or WER values suggest irregular handwriting patterns, which often align with the CNN's detection of dysgraphia-related traits. When the CNN's feature-based analysis and the OCR's

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

error-based evaluation both indicate irregularity, the system produces stronger and more reliable predictions.

5. Experimental Results

When applied to a real dataset, the proposed system achieved strong performance. It reported an accuracy of 92 percent,

$$Precision = \frac{TP}{TP + FP}$$

meaning that out of every 100 handwriting samples, 92 were classified correctly. The precision of 90 percent indicates that

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

when the model predicted dysgraphia, it was correct in 9 out of 10 cases. The recall of 93 percent shows that it successfully detected 93 out of every 100 true dysgraphia cases. The F1 Score of 91.5 percent confirms that the system maintains a strong balance between minimizing false positives and false negatives.

5.CONCLUSION

The proposed system is designed to identify handwriting patterns associated with dysgraphia with high accuracy, ensuring that children who need support receive it early, without being unnecessarily labeled r stressed. It provides real-time feedback, so parents, teachers, and school staff can gain immediate insights from submitted handwriting samples. The platform is simple and intuitive, accessible across different devices and languages, and works even in areas with limited digital resources. Detecting signs of dysgraphia at a young age enables timely interventions such as personalized learning aids, therapy, or motor-skill activities that help children build confidence and improve academic performance. The system is also scalable, capable of handling increasing amounts of handwriting data and improving its accuracy over time, and can integrate with school or health systems for a more comprehensive support network. To make the process engaging, the platform incorporates playful digital activities that not only support early screening but also provide ongoing practice and reinforcement, making learning both effective and enjoyable for children.

In addition to its core functionality, the system has the potential to support broader research in the fields of education and developmental psychology. By analyzing large volumes of anonymized handwriting data, researchers can gain insights into early markers of learning difficulties and better understand how these challenges manifest across different age groups, cultures, and educational environments. These findings can inform the development of more inclusive curricula and targeted intervention programs, ultimately contributing to a more equitable and supportive educational landscape.

Looking ahead, the system can be further enhanced through integration with artificial intelligence tools such as adaptive learning engines and personalized content recommendations.Furthermore, the system emphasizes privacy and ethical data handling, ensuring that all handwriting samples and user information are securely stored and processed in compliance with data protection standards.

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