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A Unified AI Model for Supporting Dysgraphia Learners Using Visual Scaffolding Techniques: A Systematic Literature Review

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ABSTRACT

Dysgraphia, a neurodevelopmental disorder affecting handwriting fluency, letter formation, and motor coordination, poses significant challenges for learners, particularly in early education settings. While advances in artificial intelligence (AI) and deep learning have enabled accurate dysgraphia detection through handwriting analysis, current models largely function in isolation, offering limited post-diagnostic support. This systematic literature review (SLR) explores recent developments from 2015 to 2024 in AI-based dysgraphia prediction, handwriting feature extraction, and visual scaffolding interventions. Following the PRISMA 2020 methodology, 35 peer-reviewed studies were analyzed across major databases, revealing high classification accuracies from models such as CNNs, LSTMs, Random Forest, and DenseNet. However, few studies bridge diagnosis with adaptive educational support. The review identifies a significant gap in integrating real-time classification systems with visual scaffolding strategies tailored to learner profiles. It proposes the need for a unified AI Model that not only automates dysgraphia detection but also personalizes and dynamically adapts visual scaffolding support based on individual handwriting challenges. Such a model would align with Vygotsky's Zone of Proximal Development and modern cognitive load principles, enhancing inclusive learning environments through intelligent, data-driven intervention systems.

KEYWORDS; -*Dysgraphia, Handwriting Analysis, Visual Scaffolding, Deep Learning, Adaptive Learning*

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I. INTRODUCTION

Dysgraphia is a specific learning disability that impairs a learner's ability to produce clear, legible, and organized handwriting. It affects fine motor skills, spatial coordination, and the cognitive processes involved in writing, leading to difficulties with letter formation, spacing, alignment, and writing fluency [7][2]. These challenges can severely hinder academic achievement and diminish learner confidence, especially in early education stages. Traditional interventions such as occupational therapy and handwriting practice offer partial support but are resource-intensive, subjective, and often inaccessible in low-resource learning environments [4].

While recent advances in artificial intelligence (AI) and deep learning have enhanced dysgraphia prediction by automating handwriting classification, most existing models function in isolation. They often focus solely on detection without providing structured, individualized support strategies for learners' post-diagnosis [24][3]. Moreover, although computer vision techniques such as OpenCV enable detailed handwriting feature extraction—such as spacing inconsistencies, slant deviation, and contour abnormalities—these insights are rarely linked to pedagogical interventions [38].

From a learning theory perspective, Vygotsky's Sociocultural Theory and his concept of the Zone of Proximal Development (ZPD) offer a powerful framework for designing educational interventions that bridge the gap between diagnosis and support. Specifically, building on the general scaffolding principles described by [40] and the Six-Level Scaffolding Framework proposed by [32] modern dysgraphia interventions have evolved to incorporate visual scaffolding techniques tailored to handwriting support. These include guided tracing, structured visual cues, feedback loops, and adaptive writing templates, which collectively assist learners in overcoming motor coordination and spatial challenges commonly associated with dysgraphia.

There is, therefore, a critical need for a unified model that combines three core components: (1) automated dysgraphia detection using deep learning classifiers, (2) detailed handwriting feature analysis and (3) tailored visual scaffolding aligned with each learner's needs. Such a model would not only diagnose dysgraphia with high accuracy but also deliver personalized educational support in real-time, particularly beneficial for inclusive and under-resourced classrooms.

This literature review explores the current state of research in AI-based dysgraphia prediction, handwriting analysis, and visual scaffolding techniques. It identifies methodological gaps and proposes the integration of these components into a cohesive, intelligent framework for supporting dysgraphia learners.Accordingly, this study seeks to answer the following research question:

How effective are current AI-based models in supporting dysgraphia learners through integrated handwriting analysis and visual scaffolding–based personalized intervention strategies?

II. METHODOLOGY

This study employed a Systematic Literature Review (SLR) to examine how existing research integrates dysgraphia prediction techniques with visual scaffolding strategies to support learners struggling with handwriting difficulties. The SLR approach was selected for its structured, transparent, and replicable methodology, which ensures a comprehensive and unbiased synthesis of relevant academic work. To uphold international standards, the review process was guided by the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework [30], which organizes the review into four phases: identification, screening, eligibility, and inclusion.

The review began with a broad search across five major academic databases: Web of Science, Scopus, ERIC, Google Scholar, and ScienceDirect. These databases were chosen for their extensive coverage of scholarly work in artificial intelligence, educational technology, learning disabilities, and handwriting analysis. Boolean search strings were constructed using keywords such as “dysgraphia,” “dyslexia,” “handwriting recognition,” “handwriting analysis,” “deep learning,” “visual scaffolding,” and “predictive models.” These terms were combined using Boolean operators (AND, OR) to ensure that the search captured studies relevant to both the technological and pedagogical dimensions of dysgraphia-related research. The initial search yielded 2,700 articles.

To refine the results, a series of exclusion filters were applied. Duplicate entries (n = 600) were removed first, followed by the elimination of non-peer-reviewed records such as theses, conference abstracts, and opinion pieces (n = 500). Additionally, studies published before 2015 (n = 400) were excluded to ensure the review focused on the most current and innovative approaches. This filtering process resulted in 1,200 studies advancing to the screening phase.

During the screening phase, the titles and keywords of the 1,200 remaining articles were examined. Articles unrelated to dysgraphia, such as those focused solely on dyslexia, ADHD, or general educational technology without handwriting components, were excluded. This led to the removal of 600 studies. The remaining 600 articles were subjected to abstract-level screening to assess their alignment with the study’s objectives. Only studies that addressed dysgraphia prediction, intervention strategies, or both were retained, resulting in 200 articles selected for full-text review.

The eligibility phase involved a comprehensive review of the full texts of these 200 articles. Studies were considered eligible if they: (1) focused on the prediction or diagnosis of dysgraphia using handwriting data and AI-based techniques; (2) proposed or evaluated intervention strategies, particularly those involving visual scaffolding or learner-centered instructional support; or (3) integrated both prediction and support within a unified framework. Articles that used unrelated technologies such as EEG, fMRI, or eye-tracking without handwriting input were excluded, as were those addressing general learning disabilities without relevance to dysgraphia. After applying these criteria, 105 articles were deemed eligible for inclusion.

In the final inclusion phase, each of the 105 eligible articles was evaluated for quality. Priority was given to studies published in high-impact journals (Scimago Q1/Q2) and those that demonstrated empirical rigor, sound methodology, innovative approaches, and a clear focus on learner outcomes. Following this assessment, 70 articles were excluded due to redundancy, methodological weaknesses, or insufficient relevance. The final set of 35 peer-reviewed articles was included in the review.

Among these 35 articles, some focused exclusively on dysgraphia prediction models using machine learning or deep learning, others addressed intervention strategies, particularly visual scaffolding or adaptive instructional tools, and a few explored both aspects. However, only a very small number of studies attempted to combine prediction and support strategies within a single integrated model. This highlights a significant gap in current research and reinforces the contribution of the present study, which seeks to develop a unified framework that integrates AI-based handwriting analysis for dysgraphia detection with personalized visual scaffolding for learner support.

The flow of this review process is summarized in the PRISMA 2020 Flow Diagram as shown in Figure 1, which outlines the number of records identified, screened, assessed for eligibility, and ultimately included in the final synthesis. This visual representation supports transparency and traceability across all stages of the review. Additionally, Table 1 presents the inclusion and exclusion criteria used to guide article selection, ensuring methodological consistency and clarity in the selection process.By combining technological and pedagogical perspectives, this methodology provides a solid foundation for identifying research trends, isolating gaps, and informing the development of a novel AI-driven model that supports both the diagnosis and instructional scaffolding of dysgraphia learners.

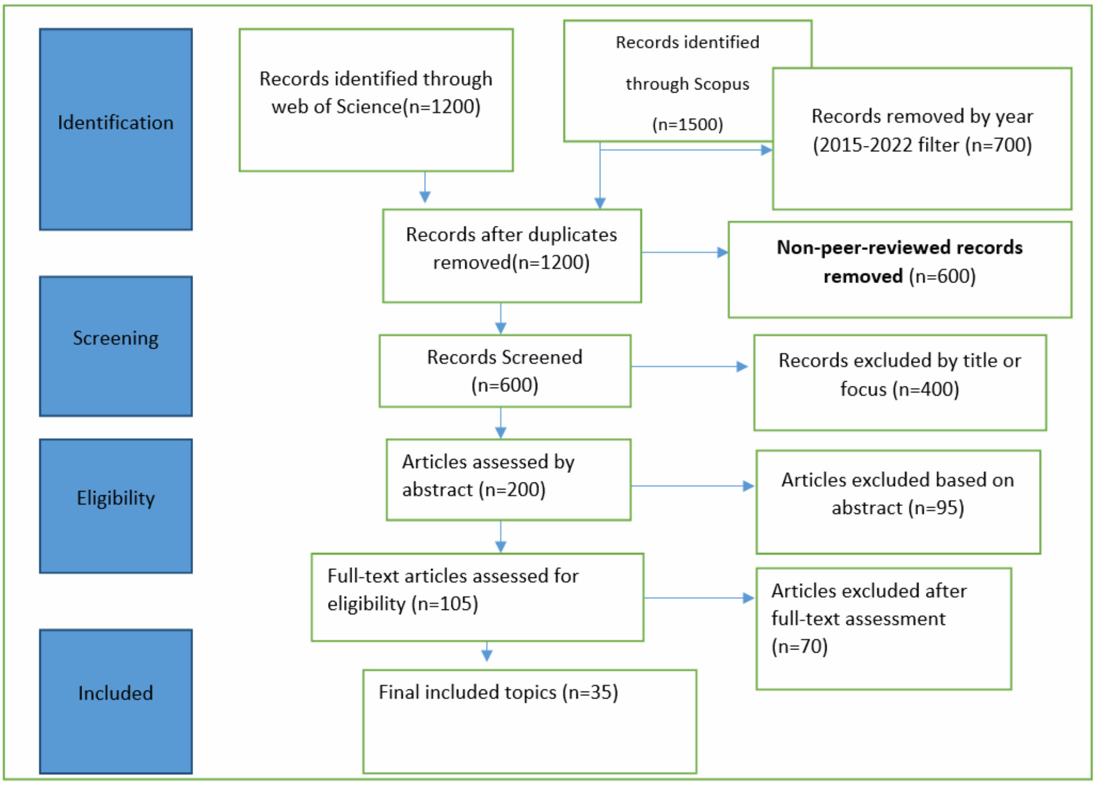

Figure 1: PRISMA 2020 Flow Diagram

To ensure methodological rigor and consistency in the review process, specific inclusion and exclusion criteria were established prior to full-text analysis. These criteria were systematically applied during the eligibility and inclusion phases to determine whether a study would be retained or excluded. The criteria addressed aspects such as publication type, language, methodological relevance, technological focus, and the presence of either predictive or intervention-based components. Table 1 summarizes these criteria,

Criterion	Inclusion Criteria	Exclusion Criteria
Publication Year	Studies published between **2015 and 2025**	Studies published **before 2015**
Language	Studies written in **English**	Studies written in **non-English languages**
Peer-Review Status	**Peer-reviewed journal articles**	Non-peer-reviewed works (e.g., theses, opinion pieces, preprints, conference abstracts)
Technological Focus	Use of **AI, machine learning (ML), or deep learning (DL)** for handwriting analysis	Studies using only traditional statistical methods or unrelated technologies
Disorder Specificity	Focus on **dysgraphia** (and selectively **dyslexia**, if handwriting-focused)	Focus on other disorders such as **dyscalculia, ADHD**, or general learning disabilities
Data Input Type	Use of **handwriting-based data** (e.g., images, stroke data)	Use of **EEG, fMRI, eye-tracking**, or speech-based inputs without handwriting data
Support/Intervention	Inclusion of **instructional support**, such as **visual scaffolding strategies**	Absence of any **intervention model or learner support mechanism**
Empirical Rigor	Presentation of **results, model evaluation, or theoretical frameworks**	Studies lacking empirical findings or methodological clarity

Table 1: Inclusion and Exclusion Criteria

This table reflects the criteria that ensured only methodologically robust, relevant, and focused studieswere included in the review. It also highlights the careful distinction made between general learning disability research and work specifically addressing dysgraphia through AI-enabledprediction and/or scaffolding-based interventions. The application of these criteria was vital in building a credible knowledge base to guide the development of the proposed unified model in this study.

III. LITERATURE REVIEW

Recent advancements in machine learning (ML) and deep learning have introduced powerful automated solutions for detecting dysgraphia through handwriting analysis. These models, including Support Vector Machines (SVM), Random Forest, and Convolutional Neural Networks (CNN), leverage both static and dynamic handwriting features—such as pen pressure, stroke velocity, and trajectory—to offer precise diagnostic capabilities [11] Integrated into digital platforms like tablets and smart pens, these AI-driven tools facilitate real-time analysis and offer scalable, accessible diagnostic support in educational and clinical contexts [27].

Among the machine learning approaches, Extreme Gradient Boosting (XGBoost) has demonstrated notable effectiveness in dysgraphia detection tasks. [29] utilized XGBoost to analyze features such as velocity and acceleration from handwriting samples of 76 children in the Czech Republic. Despite achieving a specificity of 90%, the model's sensitivity was limited due to the small and unbalanced dataset. In contrast, [1] employed a larger, more balanced dataset and found that XGBoost outperformed traditional models like SVM and Random Forest in both accuracy and interpretability, reinforcing its utility in educational diagnostics.

Random Forest classifiers have also been widely adopted due to their high performance and resistance to overfitting. [4] employed Random Forest to analyze handwriting from 298 children using consumer tablets, achieving 96.6% sensitivity and 99.2% specificity. Subsequent studies, such as those by [13] and [16] confirmed the algorithm's robustness across larger and more diverse populations. These studies demonstrated the importance of capturing dynamic handwriting features—such as speed, pen pressure, and stroke direction—to enhance diagnostic precision.

Support Vector Machine (SVM)-based systems have also contributed to effective dysgraphia detection. [33] used SVM to classify dysgraphia handwriting from digital writing pads, achieving around 90% accuracy with data from 99 children. Similarly, [12] analyzed nearly 100 handwriting features from a large sample of 580 children, including 122 diagnosed with dysgraphia. Their SVM model demonstrated 91% sensitivity and 81% specificity, underscoring its efficacy in large-scale screening.

Ensemble methods, particularly Adaptive Boosting (AdaBoost), have been explored to further increase prediction reliability. [15][14] conducted studies in Slovakia involving 120 schoolchildren, extracting features such as pen lift, velocity, and pressure using WACOM tablets. Their findings showed that ensemble approaches could achieve up to 80% accuracy, although small sample sizes and demographic limitations affected generalizability.

Artificial Neural Networks (ANNs) have also been applied in related handwriting recognition tasks. [20] used an OCR-ANN model to detect dyslexia in Malaysian children based on eight frequently miswritten characters, achieving a 73.3% accuracy rate. [34] developed a backpropagation neural network within an Android-based app, classifying handwriting features such as pressure and spacing. Their model achieved 84.7% accuracy in binary classification and highlighted the influence of learners' familiarity with digital tools on prediction outcomes.

Deep learning-based models, particularly CNNs and LSTMs, have demonstrated superior performance in recent studies. [3] proposed a CNN model trained on 249 handwriting samples to classify dysgraphia severity, achieving an 84% accuracy rate. [27] introduced a hybrid model integrating CNN, LSTM, and Random Forest, reaching a 97.6% accuracy rate and outperforming standalone classifiers. [24] achieved 97.3% accuracy using DenseNet201, while [8] [2] reported near-perfect classification results using LSTM and CNN architectures on large, diverse handwriting datasets.

Despite these technological breakthroughs, a critical gap remains in the application of AI for dysgraphia support. While numerous studies have focused on model development and classification accuracy, few incorporate comprehensive handwriting analysis as part of the diagnostic process. Moreover, none of the models reviewed extend their capabilities to recommend or implement scaffolding interventions. This absence of post-diagnostic support limits the practical utility of these systems in educational settings and highlights a pressing need for integrated frameworks that not only detect dysgraphia but also provide individualized, adaptive support for affected learners.A summary of the performance of Classification Models for Dysgraphia Detection is shown in Figure 2.

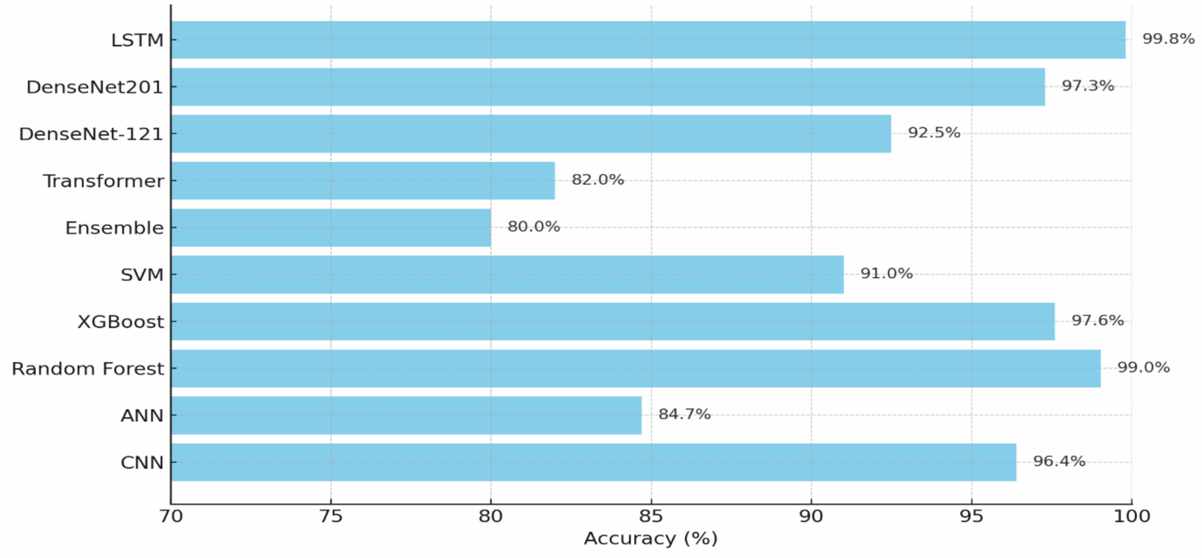

Figure 2: Performance of Classification Models for Dysgraphia Detection

Figure 2 reveals that LSTM-based models exhibit the highest accuracy (99.8%), closely followed by Random Forest (99.0%), XGBoost (97.6%), and DenseNet201 (97.3%). These models demonstrate strong potential for classifying handwriting-based dysgraphia features, especially when trained on well-curated digital handwriting datasets.

CNNs, though widely used (as shown in the pie chart), do not always outperform other deep learning models, averaging around 96.4% accuracy. Meanwhile, ANNs, Transformers, and Ensemble models fall into a lower performance tier, suggesting that while they contribute to the field, their predictive power may be limited without advanced tuning or hybridization.

This analysis supports the observation that deep feature extractors (CNNs, DenseNet) and temporal learners (LSTM) are more effective for capturing handwriting dynamics. However, integrating these models into intervention systems remains rare, and performance alone does not ensure usability unless linked with scaffold-based support frameworks.

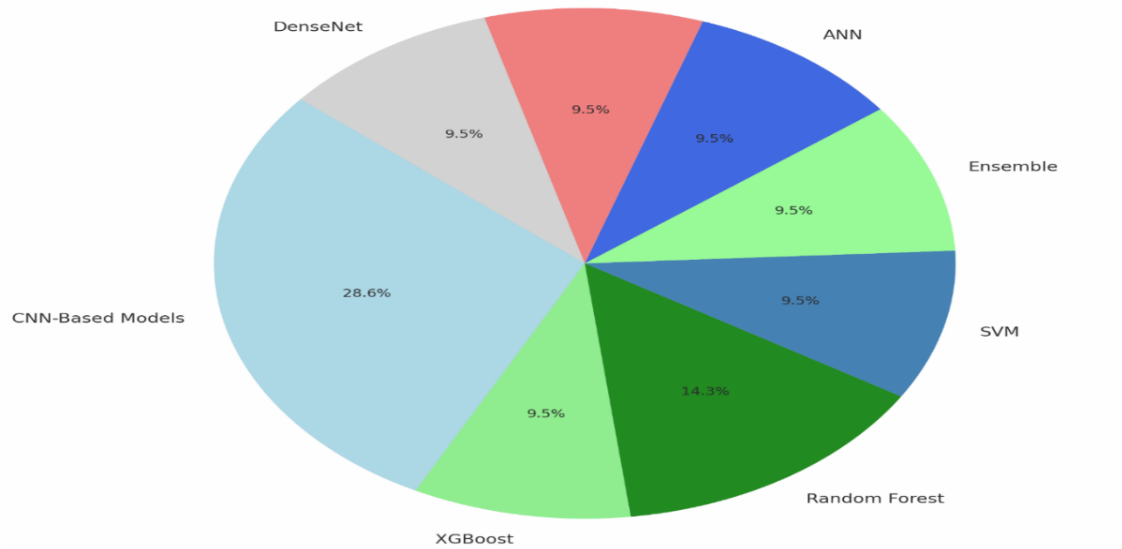

Figure 3 : Distribution of ML Models in Dysgraphia Detection Studies(2015-2024)

From the chart, it is evident that **CNN-based models** dominate the landscape, representing approximately 28.6% of all reviewed studies. This trend highlights the growing reliance on deep learning methods due to their superior performance in image-based handwriting classification tasks.

Other models like **Random Forest**, **XGBoost**, **SVM**, **ANN**, **LSTM/RNN**, **DenseNet**, and **ensemble techniques** are used less frequently, each contributing roughly equally to the remaining portion of studies. This suggests a rich diversity in algorithmic approaches, though CNNs clearly lead as the preferred choice for automated dysgraphia diagnosis

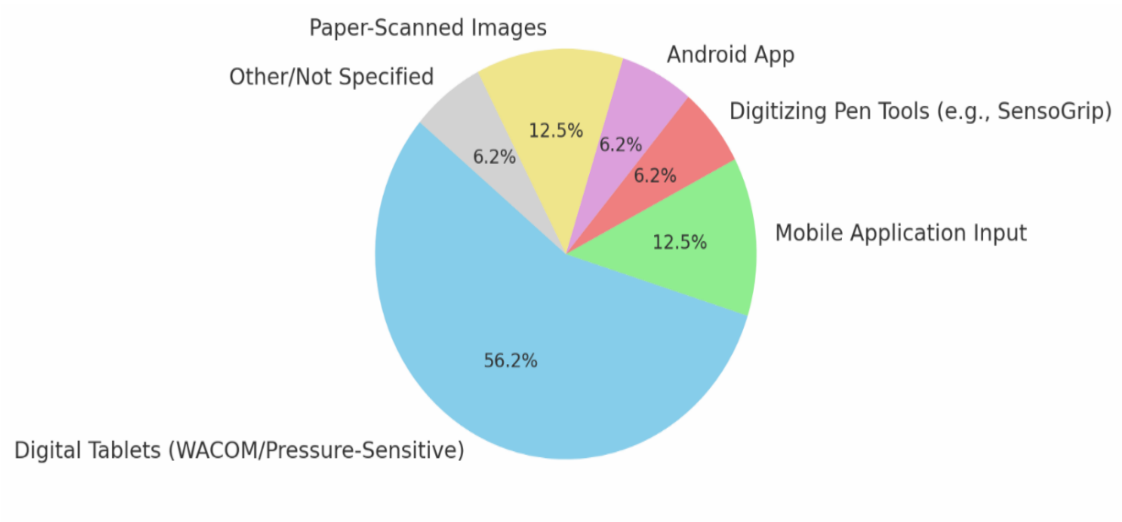

Figure 4: Distribution of Data Capture Methods in Dysgraphia Studies (2018-2024)

Figure 4 above illustrates the distribution of data capture methods employed in dysgraphia research studies from 2018 to 2024. A significant majority (56.2%) of the studies utilized digital tablets—particularly WACOM and pressure-sensitive variants—which underscores the preference for high-resolution, real-time handwriting data collection tools that can capture dynamic features like pressure, tilt, and speed.

Mobile application input and paper-scanned images each accounted for 12.5% of the studies, highlighting alternative but less sophisticated approaches to data acquisition. These methods, while accessible, may lack the depth of information necessary for advanced machine learning analysis. Specialized tools like digitizing pen systems (e.g., SensoGrip) and Android apps were each used in 6.2% of the reviewed studies, often as part of smaller or localized research efforts. Notably, a small portion (6.2%) of the studies did not clearly specify the data capture method.

This distribution suggests that while there is growing innovation in handwriting data collection, the field still heavily relies on digital tablets as the gold standard, with emerging tools offering potential for scalability and accessibility in diverse settings.

IV. HANDWRITING ANALYSIS FOR DYSGRAPHIA LEARNERS

Handwriting analysis plays a critical role in the early identification and support of learners with dysgraphia, a neurological disorder that impairs fine motor skills required for writing. Unlike traditional methods reliant on subjective teacher observations, modern handwriting analysis employs objective computational techniques to assess a wide range of handwriting characteristics—such as letter formation, stroke consistency, spacing, alignment, and [4][24]. These features reflect both the cognitive and motor planning difficulties typical of dysgraphia, providing valuable insights into the severity and nature of each learner's writing challenges.

Dynamic features such as writing speed, pen pressure, stroke smoothness, and pen lift frequency have been identified as key discriminators between dysgraphia and non-dysgraphia writing [33]. For example, [4] developed a model using Random Forest classifiers to process real-time data from pressure-sensitive tablets, achieving high sensitivity and specificity in distinguishing children with dysgraphia. Similarly, [12] utilized Support Vector Machines (SVM) on the BHK dataset and identified over 100 discriminative features, emphasizing the granularity of handwriting analysis in large-scale screening.

Advanced approaches now incorporate image-based analysis using convolutional neural networks (CNNs) and deep feature extractors like DenseNet and LSTM, which allow models to learn subtle spatial and temporal patterns in handwriting [3][27] These models analyze grayscale or binarized handwriting images, extracting contour features, slant direction, stroke width, and spatial orientation—all of which are often compromised in dysgraphia writing. [24] used DenseNet201 integrated with feature fusion strategies to achieve 97.3% accuracy in classifying handwriting samples, reinforcing the reliability of deep learning in this context.

Handwriting analysis also facilitates profiling learners by quantifying specific difficulties such as inconsistent spacing, abnormal slant, irregular letter sizing, and poor alignment. OpenCV and image processing libraries are increasingly used to detect these traits automatically from scanned handwriting samples. For instance, [16] extracted temporal and spatial features from digitized handwriting to assess variability in stroke patterns, helping to classify learners by severity level and suggesting appropriate interventions.

Despite these advancements, a key limitation persists in the lack of integration between handwriting analysis and intervention frameworks. While models can now accurately predict dysgraphia, they rarely feed their outputs into adaptive support systems that respond in real-time to a learner's needs. Studies by [8] [39] note that although AI tools can provide diagnostic insights, they are often not coupled with personalized feedback or visual scaffolding—a gap that hinders the translation of diagnostic data into actionable teaching strategies.

In summary, handwriting analysis provides a robust, objective foundation for detecting and understanding dysgraphia. However, for these tools to move beyond diagnostic use and become truly transformative, they must be integrated into learner-centered systems that dynamically scaffold support based on real-time analysis. This necessitates the development of unified models that link dysgraphia detection with adaptive visual, cognitive, and motor-based interventions.

V. VISUAL SCAFFOLDING TECHNIQUES FOR DYSGRAPHIA SUPPORT.

Visual learning techniques aid handwriting development in students with dysgraphia by simplifying tasks through visual prompts, tracing, and step-by-step guidance [28] Digital tools with visual cues and feedback improve letter formation, alignment, and fluency [31]. Visual tools support handwriting development by building motor memory through structured, repetitive practice, helping students internalize fluent handwriting movements [21].

To address motor skill challenges, techniques like modeling and guided tracing help learners replicate correct letter formation and develop muscle memory for fluent handwriting (Baker et al., 2022; James & Engelhardt, 2022). Visual-spatial aids, such as bold-lined paper and digital tools, support consistent letter size, spacing, and alignment, enhancing fluency and legibility [5][21][17]. AI-powered feedback systems offer immediate corrections, helping learners refine accuracy and build skills progressively [39].

Cognitive scaffolding techniques support dysgraphia learners by simplifying tasks with visual aids like color-coded cues and directional arrows, improving focus and memory retention [5][21][17]. Video modeling provides step-by-step demonstrations for learners to replicate at their own pace, promoting mastery through repetition [17] Visual memory exercises, such as shape and letter games, enhance retention while keeping learning engaging (Lee & Brown, 2023). AI-driven systems offer personalized feedback tailored to learners' progress, fostering continuous improvement [41].

Writing relies on cognitive processes like planning, memory, and attention, which are often disrupted in dysgraphia. Visual learning strategies, such as charts and diagrams, simplify tasks into manageable steps, enhancing focus and reducing cognitive load. These tools help learners shift from struggling with mechanics to focusing on content generation and organization [23].

Research supports that video modeling improves retention of letter formation techniques, with students gaining confidence by observing and mimicking steps until they feel ready to practice independently [35].

Interactive, game-based elements increase motivation, making practice engaging for students with dysgraphia [18]. However, overly complex tools can cause cognitive overload, disrupting fluid, automatic movement [18]. Dysgraphia often involves challenges with spatial awareness, such as letter spacing, alignment, and size consistency. Visual perceptual training has been shown to improve these skills, enhancing handwriting legibility [10]. Tools like grid paper, visual templates, and structured activities help individuals internalize spatial rules, reducing errors and inconsistencies in writing.

A study by [23] analyzed how visual learning aids such as charts, posters, and flashcards impacted students' writing skills. Their findings showed that incorporating visual aids improved reading and writing skills in secondary school students, suggesting their utility in early interventions to support literacy development.[23] developed software that used audio-visual aids to teach children aged 4–6 how to write letters. The software provided visual guides for tracing and evaluated writing through Optical Character Recognition (OCR). Results highlighted that visual tools combined with technology significantly supported early handwriting development [23].

[10] revealed that visual perception training and stroke order guidance contributed significantly to the accuracy and legibility of Chinese handwriting in children. The study provides evidence for using structured visual aids to enhance handwriting performance [10]. This directly support the concept of visual scaffolding.Studies show that scaffolding enhances handwriting development by providing structured, diminishing support, promoting independence and mastery in handwriting tasks as students transition from guided to more autonomous practice [36] Studies show that integrating video modeling, scaffolding, and game-based learning enhances fluency, accuracy, and confidence in handwriting [18].

Despite strong evidence supporting the effectiveness of visual scaffolding techniques—such as modeling, tracing, visual aids, and AI-powered feedback—in improving handwriting skills among learners with dysgraphia, current interventions often operate in isolation from diagnostic systems. While these tools enhance motor memory, spatial accuracy, and learner confidence, they are typically implemented as standalone solutions without integration into dysgraphia detection frameworks. This results in a fragmented support ecosystem that fails to offer tailored interventions based on individual learner profiles. Crucially, the absence of a unified model that combines real-time dysgraphia diagnosis with adaptive visual scaffolding limits the personalization and scalability of support. Therefore, there is a pressing need for integrated, AI-driven systems that not only detect dysgraphia but also dynamically adjust visual scaffolding strategies based on each learner's unique handwriting challenges and progress.

VI. DISCUSSION

The review of literature from 2015 to 2024 reveals that significant strides have been made in automating dysgraphia and dyslexia detection through AI-driven models, particularly those using CNN, SVM, Random Forest, and ensemble methods. Hybrid models such as CNN-SVM and CNN-LSTM-RF have demonstrated exceptional predictive performance, with accuracies exceeding 97% and, in some cases, reaching up to 99.8% (Bublin et al., 2023; Masood et al., 2023; Alqahtani et al., 2023). These high-performing models validate the feasibility of using AI for early detection of handwriting-related learning disabilities, especially when robust datasets and optimized architectures are employed.

However, a key limitation persists: the majority of AI implementations focus exclusively on detection, with minimal integration of real-time support strategies. Even where intervention is addressed, as in the case of Kaligo and similar applications, scaffolding is often static, uniform, and lacks adaptive progression tailored to individual learner needs (Park, 2024; Williams & Lee, 2023). Moreover, the disconnect between diagnostic tools and pedagogical interventions results in fragmented learning experiences for dysgraphia students.

The analysis also reveals that despite the growing body of research on visual scaffolding techniques—including guided tracing, visual checklists, and AI-generated feedback—very few studies offer a seamless pipeline that combines these tools with real-time classification and learner profiling. Most existing visual scaffolding platforms fail to implement adaptive fading, structured progression, or integration with predictive AI models. Consequently, there is a pressing need for a unified framework that not only diagnoses dysgraphia but also offers structured, individualized, and progressively adaptive learning support.

VII. CONCLUSION

This review underscores the potential of artificial intelligence to revolutionize the diagnosis and support of learners with dysgraphia. While advances in deep learning have led to highly accurate detection models, a substantial gap exists in translating these capabilities into integrated support systems. Visual scaffolding techniques—grounded in Vygotsky's ZPD and enhanced through AI—offer promising solutions, yet remain underutilized in conjunction with predictive models.

The findings highlight the necessity for unified frameworks that seamlessly bridge the gap between diagnosis and intervention. By integrating adaptive AI-driven scaffolding with precise handwriting analysis and classification models, future educational tools can deliver personalized, scalable, and effective support for dysgraphia learners. Such innovation is essential to ensure inclusive, equitable, and data-driven learning environments for all students

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