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A Survey on Handwriting Disorder Detection in Individuals with Disabilities

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Abstract: Handwritten writing is a complex biometric marker, which reflects both neurometer skill and cognitive processing abilities. The growing occurrence of writing and learning difficulties such as dysgraphia and dyslexia along with neurological conditions such as Parkinson's disease (PD), Multiple Sclerosis (MS), essential tremor (ET), and Alzheimer's disease (AD). There has been significant interest in automated handwritten based diagnostic and assessment systems. This research conducted a detailed systematic assessment of AI and Machine Learning approaches applied to handwritten analysis for prediction severity classification and monitoring of these issues. The comprehensive studies involve a broad range of approaches including CNN, transfer learning, ensemble methods, multimodal fusion frameworks, and data augmentation techniques. All analyses consistently compare the main Key performance measures including accuracy, precision, recall F1-score area under the curve of ROC sensitivity and specificity. The H2FCD model, CNN and SVM hybrid achieved highest accuracy of 99.26% and 99.33% as a result. The research gap is identified highlighting the lack of Multilanguage and multiclass severity datasets, absence of real world clinical deployment pipelines and the underrepresentation of diverse populations in training data. This review supports AI-based handwriting analysis for disability evaluation.

Keywords: Dysgraphia, Handwriting Analysis, Machine Learning, CNN, Feature Extraction

1. INTRODUCTION

Handwriting evaluation is an important tool in the diagnosis of neurological and learning impairments. The complex neurocognitive and motor skill in the handwriting that requires coordinated functioning of the central and peripheral nervous systems, which is nervous outside the central nervous system, cognitive processes such as orthographic memory, phonological encoding, and fine motor abilities. A change in handwriting patterns may be a useful biomarker for a wide range of developmental, learning and neurological conditions. Developmental disorders such as dysgraphia, dyslexia, and attention deficit hyperactivity disorder ADHD, and neurodegenerative diseases such as Parkinson's disease, multiple sclerosis, essential tremor, and Alzheimer's disease, each result in unique and detectable alterations in handwriting kinematics, morphology and dynamics [1], [2].
The Traditional handwriting measurement is conducted through a subjective evaluation by applying standardized tools such as the BHK Brave Handwriting Kinder scale, the DASH Detailed Assessment of Speed of Handwriting, and the DGM-P test. While these tools provide significant insight into the clinic, they are time consuming, subject to variable error, limited to specialist conditions, and do not capture the temporal patterns of handwriting production [3]. In addition, rising rates of learning disabilities (5–15% of school-age children worldwide) and an absence of specialists in the world have created an urgent need for scalable, objective, and standard automated tools to assess handwriting [4].
Artificial Intelligence focus on deep learning has become a transformative approach for automated handwriting analysis. CNN can derive hierarchical spatial feature from handwriting images, whereas RNN, LSTMs Model temporal patterns in continuous pen movement. Applying transfer learning from extensive image database allows for high performance even with modest clinical datasets combining ensemble methods with hybrid architectures that integrate deep feature with traditional machine learning classifiers like SVM, Random Forest enhance both accuracy and generalizability [5][6].

Dysgraphia can occur alone or in conjunction with other learning disability or even Autism spectrum disorder, dysgraphia [7], and ADHD. This highlights the timely identification of dysgraphia and related disorder issues. The early detection and intervention lessen the task and action required to correct the disorders.

The Manual assessment method entirely depends on the handwritten product for the concluding evaluation decision. [8] This enables the method to introduce several automated techniques that can utilize the dynamic characteristics of handwriting as well. Digital tablets with the ability to record multiple feature of handwriting have shown promising

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result in the associated research. Meanwhile the research indicate that that the writing experience may be different for stylus tablet setting in differ from that of a pencil paper, which is the widely used method during the skill acquisition phase.

Even with significant progress, has been made there is no comprehensive comparative review synthesizing the entire landscape of AI based handwriting analysis throughout both learning disabilities currently available. Most existing review concentrates on a single condition or metrology. These researches take this gap by thoroughly examining dysgraphia, dyslexia, ADHD, AD, MS, ET, and PD by comparing their techniques, datasets, evaluation metrics and research contributions.

2.RELATED WORK

Recent Studies in handwriting analysis has greatly progressed with the integration of artificial intelligence methodology for identifying dysgraphia and associated neurological and learning disability. Various research have examined both conventional approaches and sophisticated deep learning techniques using diverse data sources such as offline handwritten images, online tablet based input signals, and multimodal biomedical data.

a) How different model in AI such as ML vs. DL vs. Hybrid achieved in detecting handwriting based disorder detection?

b) What are the benefits and drawbacks of online vs. offline handwriting analysis system?

c) Hoe does multimodal data integration such as handwriting, ECG, voice, MRI enhance diagnostic accuracy compared to single source approaches?

d) What are the key performances in developing scalable and generalizable handwritten based diagnostic systems?

Patro and Das et al., [1] conducted a comprehensive survey involving on Parkinson's disease detection using different types of data, such as voice recordings, EEG MRI scans, and motion sensor data. The researcher analyzed multiple algorithms in machine learning and deep learning such as SVM used for classification, RF to increase the accuracy, CNN for analysis of handwriting images, RNN is designed for process the data, and GAN used for data augmentation. In this research applied among all the models the highest accuracy 100% reached in electroencephalography based models. There is a Lack of different dataset validation because the model performs under the same procedure, machine and recordings .which may not reflect in different environment and recordings.

Cohen et al., [2] focused on different feature of children handwriting for identifying attention deficit hyperactivity disorder ADHD and NON ADHD in children. In this research using handwriting in Hebrew language they have 15 evaluating steps to identify the sign of ADHD. The researchers used mathematical techniques to compare the two classes differences such as ADHD and NON ADHD and to achieved the accuracy is 0.756% indicate the performance is medium level.

Asselborn et al. [3] proposed a dysgraphia detection system using digital tablets. The research extracted 63 features derived from handwriting including static, kinematic, and pen pressure features. The system produced a sensitivity of 91% and specificity of 90%, using Principal Component Analysis (PCA) and clustering based algorithms like K-Means. The research showed the success of online handwriting assessment but was limited to a particular language and sample group.

Safura Adeela et al. [4] proposed a hybrid deep learning architecture by combining CNN and Vision Transformer VIT models for the detection of dyslexia from handwriting datasets. The research aims to detect complex visual patterns such as letter reversals, uneven spacing and variations of strokes. Although promising, the approach is still under development and is not supported by empirical evidence.

Dhekane and Ladkat et al., [5] proposed a real-time dysgraphia detection framework by combining CNN and RNN techniques with Optical Character Recognition (OCR). The research provides adaptive feedback to users with the accuracy improvement of 35% in writing fluency and 50% reduction in stroke errors. However, the research is limited by lack of large scale datasets and failure to conduct longitudinal evaluation.

Garyfallia et al., [6] proposed an overall review covering dyslexia and dyscalculia detection applying multimodal inputs like handwriting sample images, speech samples and
Virtual reality environments. They built hybrid models that combine CNN, SVM and RF and the result was a high classification accuracy of 99%. But variations in datasets and lack of standardized benchmarks hinder reproducibility.

Peng et al. [8] proposed ETSD-Net techniques for Essential Tremor detection using spiral drawings. The research is based on MobileNet-V2 architecture with attention mechanisms. It has attained high accuracy 88.44% and AUC values

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close to 0.99. The disadvantage of static images is that the dynamic characteristics of handwriting, such as speed and pressure, cannot be recorded.

In addition to these works, a number of researches were conducted on tablet based handwriting acquisition systems where dynamic features like pen pressure, stroke velocity, and pen inclination are captured. The features offer more detailed information compared with the static image based method and effectively used classifiers such as SVM, ANN, and RF. However, the need for specialized hardware that is digital tablets and smart pens restricts their accessibility.

Another research depends on the analysis of the handwriting analysis based on scanned images, where feature extraction methods like edge detection, texture analysis and contour modeling are used. These proposed strategies are less computationally demanding but often suffer from challenges in handling the temporal dynamics, resulting in less classification accuracy.

The recent trend is to employ hybrid and deep learning approaches combining CNNs with RNNs or Transformers to capture spatial and temporal features. These methodologies have performed excellently well for managing diverse handwriting patterns and individual difference. Few researches have investigated intervention-based systems, where AI techniques not only detect dysgraphia but often give more corrective feedback using gamifications and adaptive learning approaches. Such works are especially useful in educational environments for early stage detection and remediation.

In contrast, despite these enhancements, many studies remain constrained from common limitations such as small datasets, lack of cross validation on different cohorts, and limited deployment in everyday situations. Moreover, many models are tailored to specific languages or writing systems, restricting their generalizability. Overall the work shows that although much progress has been made in handwriting based disability detection there is still a need for robust, scalable and that model can be deployed in real world academics and health care settings.

Table 1: Comparative Review of AI-Based Methods for Handwriting Analysis and Neurological Disorder Detection

Authors / Year	Condition	Method	Dataset	Best Accuracy	Key Contribution
Patro & Das	Parkinson's Disease	SVM, CNN, LSTM, GAN	100 studies (PRISMA)	Voice: 94–99%; EEG: 100%	Comprehensive AI-PD review (2019–2024); micrographia identified as key biomarker[1]
Cohen et al.	ADHD (Children)	Graphological scoring; ROC	49 children	Sens. 75%; Spec. 76.2%	First use of graphology for ADHD diagnosis [2]
Asselborn et al.	Dysgraphia	PCA + K-Means (63 features)	448 children (iPad)	Sens. 91%; Spec. 90%	Introduced 5-level severity scale; kinematic features highly discriminative [3]
Dhekane & Ladkat	Dysgraphia	CNN + RNN; real-time feedback	School students (India)	92% accuracy	Real-time AI feedback loop; improved writing fluency by 35% [5]
Garyfallia et al.	Dyslexia / Dyscalculia	CNN+SVM+RF; NLP; RL	857 Malaysian students	94% (Hybrid model)	Broad AI review for learning disorders; includes gamification and Robotics [6]
Fırat et al.	Multiple Sclerosis	VGG16 CNN; Transfer Learning	426 images (Turkey)	85%; AUC 0.90	First handwriting-based AI study for MS detection [7]
Peng et al.	Essential Tremor	ETSD-Net (MobileNetV2)	315 patients; ~1000 spirals	88.44%; AUC 0.98–0.99	First remote tremor severity grading using deep learning [8]
Alqahtani et al.	Dyslexia	CNN-SVM; CNN-RF Hybrid	176,673 handwriting images	99.33% (CNN-SVM)	Highest accuracy in dyslexia detection; DL + ML hybrid approach [10]

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Sparaci et al.	Handwriting GMPs	Spearman; Wilcoxon; ANOVA	40 children (Italy)	6/9 GMPs correlated	First SBA vs VPA GMP comparison; familiarity effect analyzed [17]
Hosseini Kivanani	Alzheimer's / MCI	EfficientNet + DFC	57–91 per sub-study	90%; AUC 0.91	First multi-source handwriting fusion for dementia detection [11]
Kunhoth et al. (2023a)	Dysgraphia (Online)	AdaBoost; KNN; SVM; RF	120 children (Slovak)	80.8% (AdaBoost)	Reduced feature set (85% less); temporal & in-air features critical [22]
Adrán Otero et al.	Essential Tremor	mEMD + biLSTM; 10-fold CV	51 subjects (BIODARWO)	87.92%	mEMD outperforms 10 augmentation methods; coordinates sufficient [30]
Ramlan et al.	Dysgraphia Severity	H2FCD: ResNet-18 dual-stream CNN	136 images (Malaysia)	99.26%; Macro AUC 1.000	First multiclass severity classification; novel HistoFe feature extractor[31]
Kunhoth et al. (2023b)	Dysgraphia (Offline)	DenseNet201 + SVM fusion	120 images (Slovak)	97.3%; AUC 0.99	First public dysgraphia dataset; fusion improves SOTA by 16% [9]
Kunhoth et al.	Dysgraphia (Multimodal)	ECFF; EfficientNet-B7; SVM	~376/task (multimodal)	88.8%; AUC 0.912	First online+offline fusion; ECFF framework with SHAP explainability [12]

A comparative review of AI based methods for handwriting analysis and neurological disorder detection is summarized in Table 1.

3.MACHINE LEARNING APPROACHES FOR HANDWRITING ANALYSIS

3.1 Feature-Based Machine Learning Models

Traditional machine learning methods such as SVM, KNN, RF, and AdaBoost depend on handcrafted feature extraction. These techniques are shape, stroke structure, pressure, writing speed and temporal characteristics derived from handwriting data. The quality and relevance of the specific features will determine the quality of these models. Cohen et al. 2019 [2] proposed graphological features using ROC analysis to detect ADHD in average sensitivity and specificity. These features are computationally efficient and interpretable but these approaches require domain specific expertise for feature engineering.

3.2 Performance and Limitations of Machine Learning Models

This research has shown the promising results of the machine learning models in handwriting analysis. For example, Kunhoth et al. (2023a) [22] they used AdaBoost machine learning algorithm it can reached the result up to 80.8% accuracy with less features. However, there are some limitations in the efficiency of these models such as the poor generalization of different handwriting styles and the reliance on manually extracted features. Their performance is often not suitable for highly variable datasets since they are not able to simulate detailed spatial and temporal patterns as well as methods based on deep learning.

4. DEEP LEARNING APPROACHES FOR HANDWRITING ANALYSIS

4.1 CNN, RNN, and LSTM Architectures for Handwriting Analysis

The handwriting analysis has been dramatically transformed to Deep learning methods by allowing automatic feature extraction straight from unprocessed data. CNNs, RNNs, and LSTM networks are mainly used to extract spatial and temporal patterns in handwriting. Dhekane and Ladkat et al., 2025 [5] highlighted a CNN-RNN framework that gives real time feedback for dysgraphia identification, the result achieved 92% accuracy and increasing writing fluency.

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4.2 Transfer Learning and Performance Optimization in Handwriting Models

In this research transfer learning methodologies such as VGG16 have also been applied effectively, as given by Fırat et al. (2025) [7] the result reached 85% accuracy with an AUC of 0.90. Deep learning methods eliminate the need for manual work feature extraction and randomly reached higher accuracy, although they need large datasets and major computational resources.

4.3 Hybrid and Multimodal Approaches for Diagnosis

In Hybrid models paired the strengths of deep learning and traditional machine learning Methods to improve classification performance. Normally, deep learning methods like mainly CNNs are used for feature extraction, althrough classifiers like SVM or Random Forest are applied for final decision-making. Alqahtani et al., 2023 achieved a significant accuracy of 99.33% using a CNN and SVM hybrid model on an extensive handwriting dataset. Likewise, Garyfallia et al., 2024 [6] proposed that a grouping of CNN, SVM, and RF reached an accuracy of 94% in detecting learning disabilities. These models utilize the feature learning ability of deep networks combined with the robustness of traditional classifiers, resulting in increased performance and generalization.

4.4 Multimodal and Feature Fusion Approaches

In this approach refers to combine different types of handwriting such as online features which are pen movement and offline features are letter shape, stroke size and spacing. Both features are integrated to improve the diagnostics accuracy.

These two methods capture the information, including stroke dynamics, pressure, and visual patterns. Hosseini Kivanani et al., 2025 [11] proposed a deep feature aggregation framework using EfficientNet, the accuracy achieving 90% in Alzheimer's detection by integrating multiple handwriting sources. In addition, Kunhoth et al., 2026 [12] proposed an Efficient Cross-Feature Fusion (ECFF) techniques integrating online and offline data, achieving 88.8% accuracy with improved interpretability using SHAP analysis.

These models represent a major advancement in handwriting-based AI systems, providing increased robustness and the ability to handle complex real world scenarios. The accuracy achieved by the surveyed studies by disorder category is shown in Figure 1. While the reviewed literature is categorized by disorder type in Figure 2. Furthermore, Table 2 provides a summary of detection methods used in the surveyed studies.

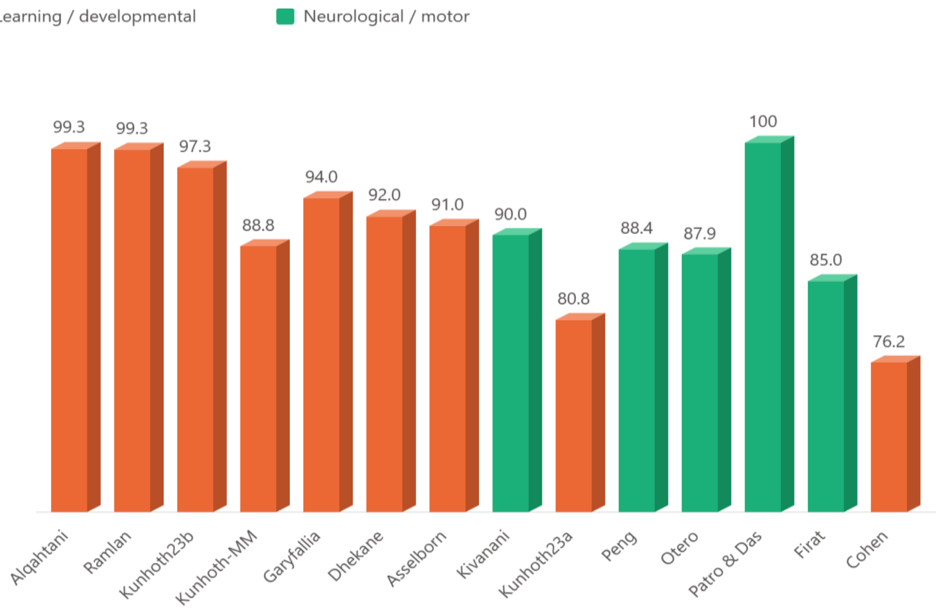

Figure 1: Accuracy Achieved Across Studies, Grouped by Disorder Category

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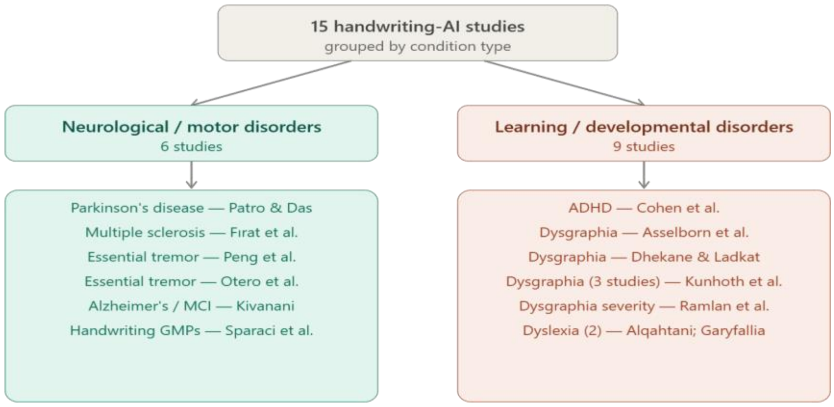

Figure 2: Categorization of Handwriting AI Literature Based on Disorder Type

Table 2: Overview of Detection methods across the Surveyed studies

Study	SVM	CNN	RNN / LSTM	GAN	Transfer learning	Hybrid fusion	Classical ML	Statistical tests
Patro & Das (Parkinson's)	✓	✓	✓	✓				
Cohen et al. (ADHD)								✓
Asselborn et al. (dysgraphia)							✓	
Dhekane & Ladkat (dysgraphia)		✓	✓					
Garyfallia et al. (dyslexia)	✓	✓					✓	
Firat et al. (MS)		✓			✓			
Peng et al. (tremor)		✓			✓			
Alqahtani et al. (dyslexia)	✓	✓				✓		
Sparaci et al. (GMPs)								✓
Kivanani (Alzheimer's/MCI)		✓			✓			
Kunhoth 2023a (dysgraphia)	✓						✓	
Otero et al. (tremor)			✓					
Ramlan et al. (dysgraphia)		✓			✓			
Kunhoth 2023b (dysgraphia)	✓	✓			✓	✓		
Kunhoth (multimodal)	✓	✓			✓	✓		

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Table 3: Comparative Analysis of AI-Based Findings across Learning Disorders and Neurological Conditions

Condition / Disorder	Key Common Findings
Dysgraphia	Motor skill analysis, kinematic features, and digital tablet-based methods are widely used for assessment. Deep learning models, particularly CNNs, consistently outperform traditional machine learning techniques in image-based analysis. [3]
Dyslexia	Hybrid approaches combining CNN with traditional ML models (e.g., CNN-SVM, CNN-RF) achieve higher performance than standalone CNNs. Vocabulary and semantic processing play a crucial role in intervention effectiveness.
Parkinson's Disease	Multimodal AI systems integrating voice, EEG, MRI, and sensor data provide the highest diagnostic accuracy. Handwriting analysis, especially micrographia, serves as an important biomarker. [15]
ADHD	Graphological analysis offers moderate diagnostic capability. Motor planning difficulties observed in ADHD show similarities with dysgraphia-related impairments. [2]
Multiple Sclerosis	Initial studies using AI for handwriting analysis in MS show promising results, with VGG16 CNN achieving approximately 85% accuracy using handwritten paragraph images.[7]
Essential Tremor	Spiral drawing analysis combined with deep learning enables non-invasive and remote severity assessment. Data augmentation techniques such as mEMD are crucial for handling limited datasets. [30]
Alzheimer's Disease / MCI	Multi-source handwriting data fusion (e.g., DFC) improves classification performance over single-source methods. EfficientNet models remain effective even with reduced training data (50%). [11]
Dyscalculia	Limited AI-based solutions currently exist. Systematic Literature Review (SLR)-based approaches report high accuracy (up to 99%), but lack validation for generalization. Gamified learning methods show potential for improvement.[6]

In Table 3 provides a Comparative Analysis of AI Based Findings across Learning Disorders and Neurological Conditions. It highlights the methods used, key findings and their applications across different learning disorders and neurological conditions.

5. DISORDERS AND ITS METHODS

5.1Deep Learning Methods for Dysgraphia Detection

Asselborn et al., [3] Dysgraphia is one of the most thoroughly researched disorders in handwriting analysis. Research reveals that motor impairments, irregular stroke formation, and reduced handwriting fluency are key indicators. In modern techniques depends on kinematic features which is writing speed, pressure, and stroke timing, frequently captured using digital tablets. Deep learning models, particularly CNNs, have described better performance in analyzing handwriting images aggregate with classical machine learning methods. These methods automatically extract critical spatial features, and most effective for dysgraphia detection.

5.2Feature-Based Methods for Dysgraphia Detection

Devi and Kavya et.al., [13] highlighted an end-to-end CNN neural network architecture for classifying the handwritten images into normal and abnormal classes. The author developed to identify dysgraphia by using the integration of handwritten data and geometric feature obtained through Kekre Discrete cosine mathematical approach. The extracted features were effectively employed in the feature learning process of deep transfer learning focused on dysgraphia detection. The Kekre Discrete Cosine Transform with Deep Transfer Learning "K-DCT-DTL" method outperformed exposed techniques. Particularly, the proposed "K-DCT-DTL" method reached the highest accuracy of 99.75%, it indicating the effectiveness and performance of the proposed methodologies.

5.3Hybrid AI-Based Handwriting Analysis for Dyslexia

Alqahtani et al., [10] Dyslexia related handwriting analysis concentrates on multimodal feature. This research indicates that proposed models, like CNN integrate with Support Vector Machine CNN-SVM or Random Forest CNN-RF, produce higher accuracy than single model by utilizing both deep feature extraction and efficient classification. Similarly, vocabulary understanding and semantic processing are essential for increasing intervention strategies. This highlights the importance of integrating handwriting analysis with language-based assessments.

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5.4 Handwriting Based Detection of Dysgraphia and Dyslexia

Mercedes Baggett et al., 2023 [16] focuses on identifying dysgraphia and dyslexia through handwriting analysis. Dysgraphia is a writing disorder that affects motor skills, although dyslexia mainly affects reading but also affect writing patterns. The research highlights key handwriting characteristics such as irregular letter formation, inconsistent letter spacing, poor alignment, and decreased writing fluency. It focuses the importance of both kinematic features like speed, pressure, and stroke timing and spatial features such as letter shape and size. In advanced techniques use machine learning and deep learning models, Especially CNNs, this automatically identifies complex handwriting features. This research indicates that merging motor and visual features, particularly using digital tools for data collection; significantly enhance the accuracy of early identification.

5.5 Multimodal AI-Based Handwriting Analysis for Parkinson 's disease Detection

Patro and Das et al., [1] Handwriting analysis is an essential method for detecting Parkinson's disease, especially through the study of micrographia which is progressively smaller handwriting. The most efficient model is multimodal AI models that merging handwriting data with other type of signals such as voice recordings, EEG, MRI, and sensor data. These merging techniques the result reached very high diagnostic accuracy. Handwriting provides a simple, non-invasive biomarker that support data collection and analyzed.

5.6 Feature Analysis and Machine Learning Approaches for Early Detection of Parkinson's Disease

Jeferson David Gallo Aristizabal et al., 2025 [15] investigates the use of handwriting analysis for early identification of Parkinson's disease, a neurological disorder impacting movement and motor function. One of the early indicators of PD is micrographia, characterized by decreased letter size and inconsistent writing patterns. This research identifies important signs such as tremors in strokes, irregular writing speed, impaired motor coordination, and difference in pressure. It use both kinematic features such as velocity, acceleration, pressure and static features like shape, spacing, size for analysis. Several machine learning models like Support Vector Machines and Random Forests, among these deep learning models such as CNNs and RNNs, are implemented to increase detection accuracy. This research summarize that handwriting analysis is a noninvasive, low cost, and easy method for early identification of Parkinson's disease.

5.7Attention Deficit Hyperactivity Disorder (ADHD)

Cohen et al., [2] Handwriting analysis in ADHD reveals motor planning and execution difficulties, similar to the characteristics found in dysgraphia. The average diagnostic performance of graphological analysis techniques indicates that handwriting alone may not be sufficient to provide an accurate diagnosis. However it can also be used as a supportive method when combined with behavioural and cognitive assessments.

5.8 Multiple Sclerosis (MS)

Firat et al., [7] Handwriting analysis for Multiple Sclerosis is still in a developing stage. Initial research using deep learning models such as VGG16 CNN shows results with around 85% accuracy. These features analyze the sample images of the hand written text to detect mild motor problems associated with MS. These findings are necessary, but more large-scale research is needed to verify these findings.

5.9 Essential Tremor

Adran Otero [30] Essential tremor is a specific neurological disability which directly impacts handwriting and drawing to extract the severity by using the features like line deviation, shakiness, speed variation, or amplitude of unwanted oscillations. Deep learning techniques can process these patterns to allow non-invasive and remote diagnosis. Due to smallest dataset availability, data augmentation techniques like multi-empirical mode decomposition (mEMD) are necessary to improve performance of the model and generalization.

5.10 Alzheimer's disease / Mild Cognitive Impairment (MCI)

Kivanani et al.,[11] The Handwriting analysis for Alzheimer's disease and MCI benefits substantially from multi-source data fusion methods, which is Deep Feature Concatenation. These models merge different handwriting features to increased classification accuracy. Methodologies such as EfficientNet have demonstrated effective even when trained on smaller datasets, making them ideal for real world application where the data availability is limited.

5.11 Dyscalculia

Garyfallia et al. [6] Dyscalculia has received relatively limited focus in AI-based handwriting research. In the existing research, is based on Systematic Literature Reviews, report reached very high accuracy up to 99%, but these approaches limited real-world validation and generalization. Emerging methods suggest that gamified learning domain might boost both diagnosis and intervention effectiveness.

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Artificial Intelligence plays an essential role in support for those suffering from a disorder in the academic, health organization and employment sectors. Artificial intelligence driven handwriting analysis systems can aid in early identification and personalized interventions. However, concerns remain regarding algorithmic bias, which may lead to unequal outcomes because the dataset doesn't contain enough variety, Therefore, it is essential to design inclusive and ethical AI systems that ensure fairness and accessibility for all users.

Table 3: Top 7 High-Performance Studies in Handwriting Analysis

Author(s) & Year	Feature Extraction	Model / Classifier	Performance Summary
Patro & Das (2025)	MFCC, spectrograms (voice); PSD (EEG); radiomic (MRI); motion features	SVM, RF, KNN, CNN, LSTM, RNN, GAN, Ensemble	EEG: 99–100%; Voice: 94–99%; MRI: up to 100% [1]
Alqahtani et al. (2023)	CNN based deep spatial features (512-d vector)	CNN, CNN SVM, CNN RF	CNN-SVM: 99.33%; CNN: 98.71%; RF: 98.44% [10]
Ramlan et al. (2026)	ResNet-18 structural + histogram features (feature fusion)	SVM, KNN, RF (Fusion model)	Accuracy: 99.26%; Macro AUC: 1.000 [31]
Peng et al. (2025)	Spiral image features with attention mechanism	ETSD-Net (MobileNetV2 + Attention)	Accuracy: 88.44%; AUC: 0.98–0.99 [8]
Asselborn et al. (2020)	63 features: static, kinematic, pressure, tilt	PCA + K-Means clustering	Sensitivity: 91%; Specificity: 90% [3]
Dhekane & Ladkat (2025)	Stroke dynamics, spacing, pressure, OCR features	CNN + RNN	Accuracy: 92%; Fluency improved by 35%; Errors reduced by 50% [5]
Fırat et al. (2025)	VGG16 feature maps (transfer learning)	VGG16 CNN	Accuracy: 85%; AUC: 0.90 [7]

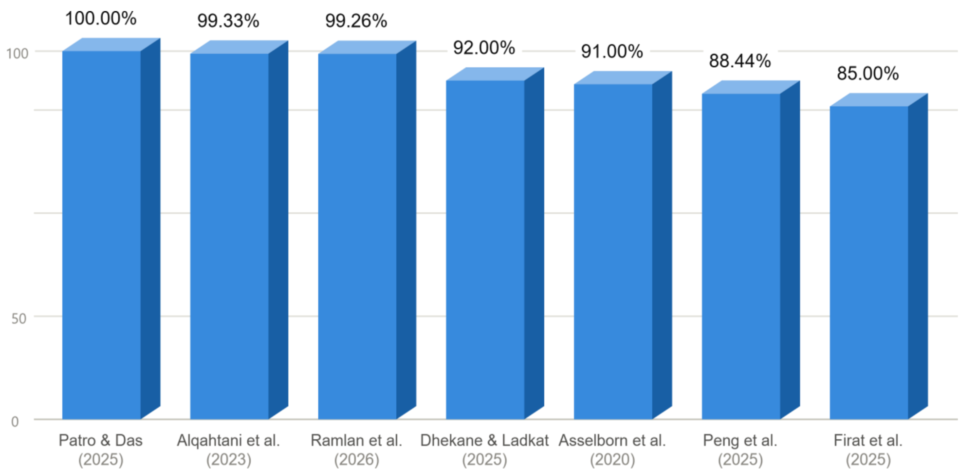

Figure 3: Comparison of Best Reported Accuracy by Study

The figure 3 above compares the best reported accuracies in selected research on the analysis of handwriting and dysgraphia identification. It shows the performance accuracy achieved using several methods and proposed recent trends in the field. The differences in accuracy are due to the differences in the datasets, features and classifiers and indicate the importance of scalable and generalize methods for practical applications.

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The Table 3 outlines the significant progress in handwriting based disability detection using machine learning and deep learning techniques. Das et al., 2025 [1] demonstrated the effectiveness of multi source framework by fusing voice, EEG, MRI, and sensor data, the accuracy obtained was exceptionally high, even with EEG signals up to 100%, this highlights the power of fusion of multiple data sources.
Alue that Alqahtani et al. 2023 [10] proposed methodologies that integrate two machine learning techniques CNN and SVM. the CNN extracts feature automatically from handwritten images, the SVM classify the handwritten images into final classification. Each combination is known as hybrid architecture. Additionally Ramlan et al. (2026) [31] introduced a feature fusion technique such as integrates structural and histogram based features it describes geometry shape of handwritten images and distribution gradients of images. These methodologies reached the accuracy 99.26 it indicates perfect consistency and accurate.
Similarly, Peng et al., (2025) [8] gives distinctive features such as stroke patterns, letter shapes, spacing, or irregular formations. this model reached higher accuracy 0.98 and0.99 because it makes more accurate classifications and reduces misclassification. Asselborn et al. 2020 [3] demonstrated extensive feature set engineering by capture 63 handwriting features, achieving moderate results with 91% sensitivity and 90% specificity, specifically in online handwriting analysis. Dhekane and Ladkat et al., 2025 [5] designed a real time CNN and RNN system that not only identify dysgraphia with 92% accuracy but also increased in writing fluency by 35% and decreased errors by 50%, indicating its practical applicability in academic settings. Finally, Firat et al. 2025 [7] highlighted the utility of transfer learning using the VGG16 model, reached an accuracy of 0.90, which is particularly beneficial when it is working with smallest datasets. Overall, these researches describe that the modern techniques using multi source data, hybrid modeling, feature fusion, attention enhanced architecture and automated feedback systems significantly improve the accuracy, robustness and usability of the handwriting analysis systems.

6. CONCLUSION

This research demonstrated a detailed evaluation of several Machine Learning and Deep Learning approaches used for handwriting based deficiency and classification tasks. Particularly examines on neurological disability such as dysgraphia and ADHD. Classical machine learning techniques such as SVM, KNN, and Random Forest have shown positive results when paired with handcrafted features. However, these methodologies usually depend on feature engineering and can lack robustness across various data sets. On the other hand, deep learning models, such as CNNs, RNNs and hybrid architectures, have shown better performance by automatically learning complex feature representations from raw handwriting data. In recent years, multisource systems and feature fusion method have additionally increased the classification accuracy and generalization performance.
In summaries, this research indicates that although deep learning techniques are leading the current advancements, the integration of traditional approaches with advanced architectures and the investigation of hybrid models can offer more reliable and scalable solutions. Future research should aim at developing robust, explainable and clinically applicable systems to enhance early diagnosis and intervention. Future directions propose a multi modal combining AI, explainable frameworks and inclusive co-designed assessment tools. This review offers a consolidated reference for researchers, clinicians, and developers operating at the intersection of AI and handwriting-based disorder assessment.

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