Automated Screening of Cognitive Skills Impairment via Handwriting Kinematics

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***Abstract*—The detection of cognitive impairment has traditionally relied on manual neuropsychological tests that are time-consuming, subjective, and resource-intensive. To address this limitation, we propose an automated framework that leverages handwriting kinematics to identify domain-specific cognitive impairments. The method extracts stroke-level features—such as speed, acceleration, pressure, jerk, and temporal dynamics—from digitized handwriting samples and maps them to cognitive domains using independent XGBoost classifiers. For evaluation, we used the publicly available DARWIN data set of 174 participants, applying 5-fold stratified cross-validation to distinguish healthy from impaired subjects in seven domains: Fine Motor Coordination, Sensory Integration, Processing Speed, Visual Planning, Executive Function & Sequencing, Working Memory load, and Attention & Inhibition. Experimental results demonstrate AUC scores ranging from 0.75 to 0.91, with the best performance in Sensorimotor Integration (0.91) and the lowest in Visuospatial Planning (0.75). This study contributes to a scalable, interpretable handwriting-based assessment framework that explicitly links digital biomarkers to cognitive domains, offering a promising tool for early, domain-specific cognitive screening.**

Keywords: handwriting analysis, cognitive screening, motor kinematics, digital biomarkers, stroke-level characteristics, XGBoost

I. Introduction

Assessment of cognitive skills such as fine motor coordination, sensorimotor integration, processing speed, visuospatial planning, executive function, working memory, and attentional control is critical for early detection of mental and neurological disorders(MNDs). Traditional neuropsychological batteries, however, often require extensive clinician time and are subject to inter-rater variability [1]. In contrast, digital handwriting analysis offers an objective, low-cost, and ecologically valid proxy for these domains, since writing engages distributed cortical and subcortical networks underlying motor execution and higher-order cognition [2].

Handwriting kinematics—captured via pen-position trajectories, pressure sensors, and timing—have been shown to reflect distinct cognitive processes. For example, reduced *mean speed on paper* and increased *pressure variability* index impairments in fine motor coordination [3], whereas prolonged *air-time to paper-time ratios* and altered *pen-down counts* correlate with sensorimotor integration deficits [4]. Similarly, global *total writing time* and *on-paper geometric mean radial tangential velocity* serve as markers of overall processing speed [5], while measures of *displacement index* and *stroke extension* capture visuospatial planning abilities [6]. Features such as mean jerk in air and on paper have been closely associated with executive sequencing and motor planning processes. This is supported by models of handwriting that describe motor planning as an optimization process that minimizes jerk across strokes, suggesting that increased jerk reflects deficits in the sequencing and coordination of motor commands [7]. Additionally, increased intra-individual variability across successive strokes is a marker of heightened working memory load during writing tasks. Such variability may reflect challenges in maintaining consistent motor output while simultaneously managing cognitive demands [8]. These relationships highlight the dual cognitive-motor nature of handwriting and its potential utility for assessing subtle deficits in executive and working memory. Finally, variability in stroke pauses and pen pressure has been linked to sustained attention and inhibitory control, reflecting underlying disruptions in executive regulation and motor planning processes[9].

A stroke in handwriting refers to a continuous sequence of pen movements between a pen-down and pen-up event. Each stroke encapsulates rich kinematic data that reflects not only motor execution but also underlying cognitive processes involved in writing[10]. This study leveraged digital handwriting data to extract a comprehensive set of stroke-level features, including writing speed, acceleration, pressure variance, air time, contact duration, stroke extent, and jerk. These features were systematically grouped into cognitive domains, including Fine Motor Coordination, Sensorimotor Integration, Processing Speed, Visuospatial Planning, Executive Function & Sequencing, Working Memory Load, and Attention & Inhibition. This domain-specific feature mapping served as the foundation for our downstream machine learning analyses to detect cognitive and motor impairments.

Building on these insights, we develop and evaluate a classification pipeline that leverages stroke-level kinematic and pressure features—extracted via our top_edges procedure—to distinguish "impaired" from "not impaired" performance across seven cognitive domains. We use an XGBoost classifier with stratified k-fold cross-validation and grid-search hyperparameter tuning on a comprehensive handwriting dataset comprising 175 participants who completed standardized writing tasks. Model performance is assessed using ROC AUC, precision–recall, and confusion matrices, and we further interpret the results through feature-importance analyses. This approach offers a scalable, efficient framework for automated screening for cognitive impairment using routine handwriting samples. Unlike prior studies that rely primarily on global handwriting metrics, this work adopts a domain-aware modeling strategy that explicitly maps stroke-level features to distinct cognitive functions. This design enables finer-grained detection of cognitive impairments and improves domain-level interpretability.

The remainder of the paper is organized as follows: Section II reviews related work on handwriting-based cognitive assessments. Section III details the methodology, including dataset description, feature extraction, and model training. Section IV presents the results and analysis, and Section V concludes with a discussion on the implications and future work.

II. Related Work

Handwriting is a complex, integrative task involving motor execution and higher-order cognitive functions. It recruits distributed cortical and subcortical networks, including the primary motor cortex, premotor and supplementary motor areas, prefrontal cortex, posterior parietal cortex, basal ganglia, and cerebellum. Recent advances in digital handwriting capture technologies enable detailed analysis of handwriting kinematics, such as speed, pressure, acceleration, and spatial displacement. These analyses have emerged as promising digital biomarkers for assessing cognitive decline, a significant area of interest in neuroscience and psychology.

This section outlines the relationships between key handwriting characteristics and cognitive skills, the associated brain regions, and empirical findings. Understanding these relationships can help detect cognitive decline early, guide the development of interventions to improve cognitive function, and inform the design of assistive technologies for individuals with motor impairment.

A. Fine Motor Coordination

Fine motor coordination reflects the ability to generate smooth, rapid, and force-modulated strokes during handwriting. Slower stroke velocities, reduced acceleration during pen movements on paper, and unstable force application, as inferred from variable pen pressure, suggest bradykinesia and impaired cortical drive[11]. These motor impairments are often associated with dysfunction in the hand areas of the primary motor cortex and cerebellum, which are essential for precise motor execution and real-time error correction [12].

B. Sensorimotor Integration

Sensorimotor integration involves coordinating visual, tactile, and proprioceptive feedback with motor commands. Prolonged airborne pauses between strokes, increased contact duration on the paper surface, and frequent pen-up/pen-down transitions indicate compensatory strategies or difficulties in real-time sensory updating. Such patterns point to dysfunction in the posterior parietal cortex and somatosensory cortex, which play a central role in spatial alignment and proprioceptive mapping during writing [13], [14].

C. Processing Speed

The speed of handwriting, including the overall duration of the task and the execution time of the stroke, reflects the efficiency of cognitive–motor processing. The prolonged total writing time and the decreased radial-tangential stroke velocity suggest global cognitive slowing. These deficits are typically linked to impaired function in the prefrontal cortex and disrupted communication within basal ganglia circuits, both of which are crucial for motor initiation and temporal coordination [15], [16].

D. Visuospatial Planning

Effective handwriting relies on accurate spatial layout and trajectory planning. Indicators such as overly circuitous stroke paths and abnormal horizontal or vertical extension patterns point to inefficient visual–motor translation. These visuospatial difficulties have been associated with dysfunction in the right parietal lobe and the dorsal visual stream, which are known to support spatial orientation and perceptual-motor integration [17], [18].

E. Executive Function & Sequencing

This domain involves organizing and executing goal-directed stroke sequences. Irregularities such as abrupt fluctuations in pen acceleration (jerk) and fragmented transitions between strokes indicate disordered planning and impaired sequencing. These disruptions are often attributed to reduced activation in the dorsolateral prefrontal cortex and the supplementary motor area, which support motor planning and executive oversight [19].

F. Working Memory Load

Variability in stroke timing across a writing session may indicate elevated working memory demands. When participants show inconsistent timing patterns across strokes, it suggests difficulty in holding and updating the motor sequence in mind. This cognitive load is believed to involve the frontoparietal network, particularly the dorsolateral prefrontal cortex and the inferior parietal lobule [20], [21].

G. Attention & Inhibition

This domain refers to the ability to stay focused and control impulsive responses. Longer pauses between strokes and unstable pen pressure may indicate attentional lapses or weak inhibitory control. These processes are linked to the anterior cingulate cortex and the right inferior frontal gyrus, which support sustained attention and suppression of inappropriate motor responses [22].

Although handwriting has been used to detect cognitive impairment, most studies rely on broad measures such as average velocity or total writing time. They rarely relate handwriting features to specific cognitive domains, brain regions, or stroke-level patterns. This study addresses that gap by introducing a domain-aware framework that links handwriting features with cognitive skills and their neuroanatomical basis, using a scalable machine learning approach.:

- **Fine Motor Coordination:** Features such as mean_speed_on_paper, mean_acc_on_paper, and pressure_var reflect coordination abilities, involving the *primary motor cortex*, *cerebellum*, and *basal ganglia*[23], [24]. These features indicate the precision and smoothness of motor actions during handwriting, which are essential for efficient motor execution.
- **Sensorimotor Integration:** Metrics like air_time, paper_time, and num_of_pendown map to integration of sensory and motor information, associated with the *somatosensory cortex* and *posterior parietal cortex*[25], [26]. These features highlight the coordination of sensory input with motor output during handwriting tasks.
- **Processing Speed:** Indicators such as total_time, gmrt_on_paper, and paper_time represent task fluency, linked to the *prefrontal cortex* and *white matter tracts*[27], [28]. Faster processing speed reflects the brain's ability to analyze and respond to writing tasks quickly.
- **Visuospatial Planning:** Features including disp_index, max_x_extension, and max_y_extension relate to spatial planning, engaging the *posterior parietal cortex* and *parietal lobe*. These features assess the planning and execution of spatially organized movements during handwriting.
- **Executive Function & Sequencing:** Stroke-level features like mean_jerk and num_of_pendown capture cognitive control and order of actions, tied to the *dorsolateral prefrontal cortex (DLPFC)* and *supplementary motor area (SMA)*. These features evaluate the ability to plan and sequence the strokes involved in writing tasks.
- **Working Memory Load:** Variability in total_time across strokes reflects cognitive load, involving the *hippocampus*. Increased working memory load is associated with the brain's need to process and retain more information during writing.
- **Attention & Inhibition:** Measures such as air_time fluctuations and pressure_mean relate to attentional engagement and control, associated with the *anterior cingulate cortex (ACC)* and *orbitofrontal cortex*. These features reflect the cognitive control mechanisms that allow individuals to focus and inhibit irrelevant information during tasks.

By training individual XGBoost classifiers for each cognitive domain using the proposed feature-to-domain mapping, the pipeline can detect impairments in a domain-specific manner rather than relying on a single global prediction. This design enables the model to capture distinct cognitive–motor patterns across different functional domains and reduces the risk of masking subtle impairments that monolithic approaches may overlook. Furthermore, aligning model predictions with domain-relevant handwriting features enhances interpretability by directly linking classification outcomes to their underlying neurophysiological correlates. As a result, the proposed framework provides a more transparent and mechanistically grounded approach to handwriting-based cognitive screening, offering advantages over prior black-box or aggregate models that lack domain-level specificity and explanatory powers.

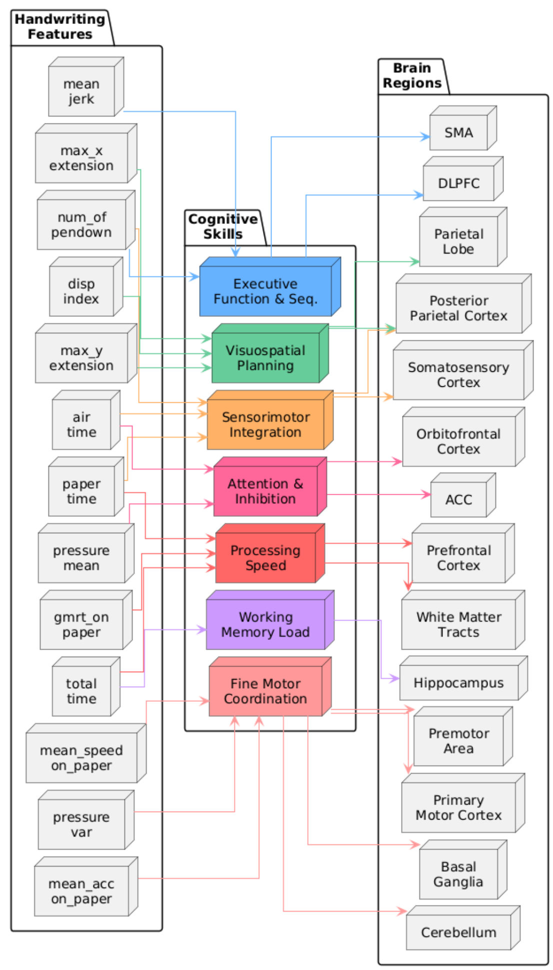

Fig. 1. Sankey diagram illustrating the mapping between handwriting-derived features, associated cognitive skills, and their corresponding brain regions. Each cognitive skill is represented with a unique color to distinguish feature-skill-region relationships.

III. Methodology

A. Problem Specification and Formulation

This study aims to automatically classify cognitive impairments using handwriting kinematics. Specifically, we aim to detect cognitive skill impairments across seven distinct cognitive domains based on handwriting-derived features. Given a set of handwriting features $\mathbf{x}_i \in \mathbb{R}^D$ for subject i, the task is to predict the cognitive status $y_i \in \{0, 1\}$, where $y_i = 0$ indicates a Healthy Control (HC) and $y_i = 1$ indicates a Patient (P).

For each cognitive domain $d \in \{1, \ldots, 7\}$, the problem is treated as a binary classification task, where the extracted features $\mathbf{x}_i^{(d)}$ corresponding to domain d are mapped to the binary label y_i. We define the feature subset for each domain as:

$$\mathbf{x}_i^{(d)} \subseteq \mathbf{x}_i,$$

where $\mathbf{x}_i \in \mathbb{R}^D$ represents the full feature vector, and $\mathbf{x}_i^{(d)} \in \mathbb{R}^{D_d}$ corresponds to the relevant features for domain d. The classification model for each domain is formulated as:

$$f_\theta^{(d)} : \mathbb{R}^{D_d} \to [0, 1],$$

where $f_\theta^{(d)}(\mathbf{x}_i^{(d)})$ represents the probability of subject i being impaired in domain d.

The optimization objective for each domain-specific task is to minimize the AUC-based loss:

$$\hat{\theta}^{(d)} = \arg\min_\theta \mathcal{L}_{\text{AUC}}\Big(f_\theta^{(d)}(\mathbf{x}_i^{(d)}), y_i\Big).$$

The AUC-based loss is chosen because it provides a robust measure of model performance, especially in imbalanced classes. Unlike traditional accuracy, AUC considers the actual positive and false positive rates across various classification thresholds. This is particularly useful in cognitive impairment classification, where the number of healthy controls and patients may not be equal. By using AUC, we ensure that our model's ability to discriminate between the two classes correctly is accurately assessed, without being biased by class imbalance.

B. Design of the Classifier

1) Feature Extraction and Selection: Features are grouped into seven cognitive domains in line with previous handwriting and cognitive research. These domains correspond to specific aspects of motor and cognitive functioning and are derived from the following handwriting features (see Table I):

For each cognitive domain, we select the relevant subset of features that best captures the characteristics of cognitive impairment related to that domain.

2) Classifier Selection: For classification, we use XGBoost ($f_\theta : \mathbb{R}^d \to [0, 1]$), a powerful and efficient gradient boosting method that has proven to perform well in supervised classification tasks. XGBoost is particularly advantageous for its ability to handle a wide range of data types and its robustness against overfitting, making it an ideal choice for our task, where feature subsets vary across cognitive domains. The model's ability to handle complex, non-linear relationships between features, its scalability to large datasets, and its speed in both training and prediction make it suitable for real-world applications such as cognitive screening. Moreover, XGBoost incorporates feature importance, which allows for better interpretability of the model, a crucial aspect in cognitive studies. We train an independent classifier for each cognitive domain.

TABLE I
DOMAIN-SPECIFIC HANDWRITING FEATURE SUBSETS

Cognitive Domain	Feature

Fine Motor Coordination[29]	`mean_speed_on_paper`
	`mean_acc_on_paper`
	`pressure_var`

Sensorimotor Integration[30]	`air_time`
	`paper_time`
	`num_of_pendown`

Processing Speed[31]	`total_time`
	`paper_time`
	`gmrt_on_paper`

Visuospatial Planning[32]	`disp_index`
	`max_x_extension`
	`max_y_extension`

Executive Function & Sequencing[33]	`mean_jerk`
	`mean_jerk_on_paper`
	`num_of_pendown`

Working Memory Load[34]	`total_time`
Attention & Inhibition[32]	`air_time` `pressure_mean`

d, as outlined in the formulation above, allowing us to focus on domain-specific patterns and improve the granularity of the classification.

C. Evaluation Procedure

1) Dataset Used for Evaluation: We use the publicly available DARWIN dataset, containing handwriting recordings from $N = 174$ participants. Each participant's data is labeled as either Healthy Control (HC) or Patient (P), and this annotation serves as the ground truth for our supervised learning tasks. We use a stratified 70/30 train-test split, maintaining class balance in both subsets.

2) Evaluation Protocol: We employ 5-fold Stratified Cross-Validation (CV) for model selection. The data is divided into five folds, ensuring each fold has a proportional distribution of HC and Patient labels. The model is trained and validated on each fold, and performance metrics are averaged across all five runs.

3) Model Selection: During cross-validation, the hyperparameters of the XGBoost classifier are tuned using a grid search to identify the configuration that yields optimal classification performance. Specifically, the number of boosting trees (`n_estimators`) is varied to balance model complexity and learning capacity. In contrast, the maximum tree depth (`max_depth`) controls the expressiveness of individual trees and helps prevent overfitting. The learning rate (`learning_rate`) regulates the contribution of each tree to the ensemble, enabling a trade-off between convergence speed and generalization. In addition, subsampling of training instances (`subsample`) and feature subsampling at the tree level (colsample_bytree) are explored to introduce randomness and improve model robustness. The optimal hyperparameter combination is selected based on the highest average ROC AUC score obtained across cross-validation folds and is used for final model evaluation.

D. Classification Pipeline

The entire classification workflow is illustrated in Figure 2. Following preprocessing and feature extraction, domain-specific feature subsets are used to train independent classifiers for each cognitive domain. Each classifier receives only the features relevant to its respective domain and outputs the probability of impairment for that domain.

The trained classifiers generate predictions (labels and probabilities) for each subject, which are evaluated using ROC AUC, precision–recall analysis, and confusion matrices. This domain-specific approach enables a fine-grained analysis of cognitive impairments across different functional areas without relying on a single global model.

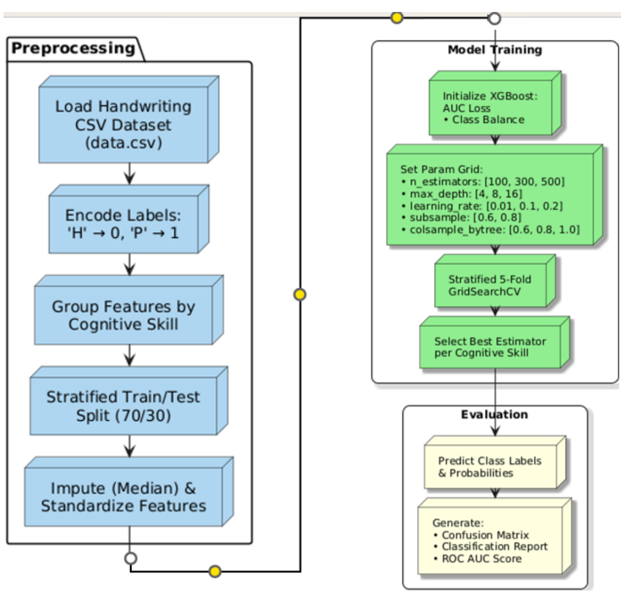

Fig. 2. Pipeline architecture for handwriting-based cognitive impairment classification using XGBoost. The process includes data preprocessing, cognitive skill-based feature grouping, and model training using stratified cross-validation and hyperparameter tuning.

IV. Results

To evaluate the efficacy of handwriting-derived features in classifying cognitive performance, we trained a separate XGBoost classifier for each cognitive domain using 5-fold stratified cross-validation. The models were assessed on a test set of 175 subjects, and performance metrics, including precision, recall, F1 score, and area under the ROC curve (ROC AUC), were calculated for each model.

TABLE II
Classification Performance Across Cognitive Domains

Domain	Precision	Recall	F1-Score	ROC AUC
Fine Motor Coordination	0.82	0.78	0.80	0.88
Sensorimotor Integration	0.80	0.89	0.84	0.91
Processing Speed	0.75	0.83	0.79	0.87
Visuospatial Planning	0.67	0.78	0.72	0.75
Executive Function & Sequencing	0.82	0.78	0.80	0.88
Working Memory Load	0.76	0.89	0.82	0.87
Attention & Inhibition	0.75	1.00	0.86	0.89

As shown in Table II, classification models achieved good overall performance across domains. The best-performing domain was *Sensorimotor Integration*, with an F1-score of 0.84 and a ROC AUC of 0.91. *Attention & Inhibition* also yielded high performance, with a recall of 1.00 and ROC AUC of 0.89. The lowest-performing domain was *Visuospatial Planning*, with an F1-score of 0.72 and a ROC AUC of 0.75. Table III summarizes group-level comparisons for handwriting kinematic and pressure features in Healthy Controls (HC) versus Patients. Several features differed significantly between groups. Patients exhibited shorter air-time ($p = 0.042$) and reduced geometric-mean radial–tangential velocities both in-air and on-paper ($p < 0.001$). Significant differences were also observed for mean writing speed ($p < 0.001$), normalized jerk both in-air and on-paper ($p = 0.020$, $p = 0.010$), mean grip pressure ($p < 0.001$), and pressure variability ($p = 0.001$). No significant differences were found in maximum horizontal extension, mean on-paper acceleration, or total task duration.

TABLE III
Group-wise means ± SE and p-values for handwriting features in HC vs. PwMS (single-column).

Feature	HC (mean ± SE)	PwMS (mean ± SE)	p-value
Air Time	50556.29 ± 12452.06	24061.89 ± 3051.61	0.042
Disp Index	0.00 ± 0.00	0.00 ± 0.00	<0.001
Gmrt In Air	259.19 ± 6.34	207.77 ± 5.52	<0.001
Gmrt On Paper	189.14 ± 3.56	151.22 ± 3.85	<0.001
Max X Extension	3716.54 ± 36.29	3792.49 ± 40.12	n.s
Max Y Extension	6201.84 ± 60.33	6489.67 ± 63.68	0.001
Mean Acc In Air	0.54 ± 0.01	0.49 ± 0.01	0.011
Mean Acc On Paper	0.15 ± 0.00	0.15 ± 0.00	n.s
Mean Gmrt	224.16 ± 4.46	179.50 ± 4.36	<0.001
Mean Jerk In Air	0.09 ± 0.00	0.08 ± 0.00	0.020
Mean Jerk On Paper	0.02 ± 0.00	0.02 ± 0.00	0.010
Mean Speed In Air	3.85 ± 0.07	3.26 ± 0.07	<0.001
Mean Speed On Paper	3.20 ± 0.07	2.49 ± 0.07	<0.001
Num Of Pendown	12.83 ± 0.25	14.82 ± 0.31	<0.001
Paper Time	9718.68 ± 205.88	13349.34 ± 355.90	<0.001
Pressure Mean	1815.08 ± 11.33	1629.38 ± 24.91	<0.001
Pressure Var	132212.45 ± 2860.30	146584.48 ± 3405.01	0.001
Total Time	60274.98 ±12511.08	37411.23 ± 3192.54	n.s

Figure 3 shows composite feature comparisons across the seven cognitive domains for Healthy Controls and Patients. Statistically significant differences were found in *Fine Motor Coordination*, *Sensorimotor Integration*, *Processing Speed*, *Visuospatial Planning*, and *Executive Function & Sequencing*. No significant group differences were observed in *Working Memory Load* and *Attention & Inhibition*.

V. Discussion

The findings show that handwriting kinematics offer a reliable and interpretable basis for screening domain-specific cognitive impairments. High performance in Sensorimotor Integration, Attention & Inhibition, and Executive Function & Sequencing suggests that features such as air-time, pen-down behavior, and jerk are sensitive to deficits in feedback processing, attentional control, and motor planning. This supports the idea that handwriting reflects an active interaction between cognition, perception, and movement rather than simple motor output.

From an HCI perspective, handwriting is a natural and low-burden input modality for implicit cognitive assessment. Unlike conventional neuropsychological tests, it can be integrated into everyday digital tasks such as note-taking or form filling. The domain-specific framework used in this study is especially valuable because it identifies affected cognitive functions instead of producing one overall impairment score.

The lower results for visual planning indicate that some cognitive processes may not be captured well by basic spatial stroke features alone. This suggests that future systems should use tasks with stronger visuospatial and planning demands. A key strength of this work is its interpretability, as handwriting features are explicitly linked to cognitive domains and neurocognitive mechanisms. This can support transparent and adaptive systems in health and education. However, the study used only one public dataset, which may limit generalizability across populations and task settings.

Overall, the study shows that fine-grained handwriting analysis can support scalable, explainable, and human-centered cognitive screening, with potential for unobtrusive early assessment in real-world settings.

VI. Conclusion

This study proposed a domain-aware framework for screening cognitive skill impairments through handwriting kinematics. Stroke-level temporal, spatial, and pressure features were extracted from digital handwriting and linked to specific cognitive domains. Independent XGBoost classifiers were then used to identify impairment across seven cognitive functions. Results showed strong performance, especially for sensorimotor integration, executive functioning, and attentional control.

An important contribution of this work is its interpretability. By connecting handwriting features with cognitive domains and their neurocognitive basis, the framework provides transparent and meaningful predictions. This is particularly important in clinical, educational, and assistive contexts where explainability is essential.

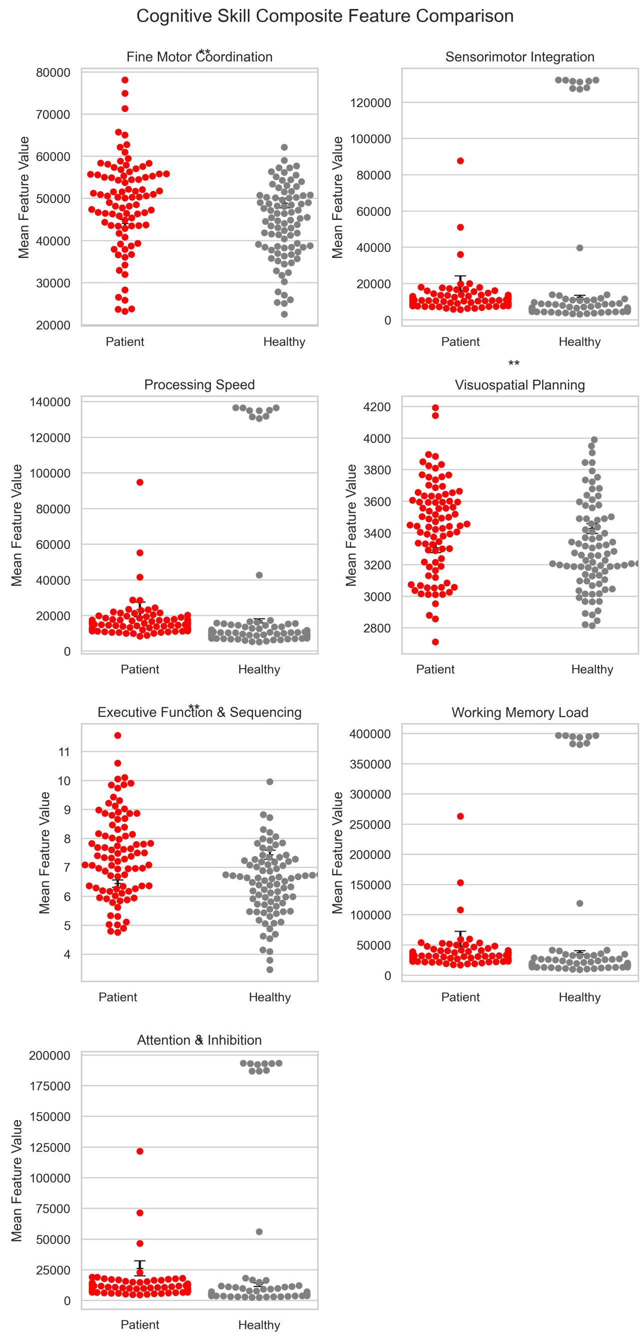

Fig. 3. Composite feature comparisons for seven cognitive domains in Healthy controls (gray) versus Patients (red). Individual subject values are shown with mean ± SE bars and significance annotations. Panels correspond to (A) Fine Motor Coordination, (B) Sensorimotor Integration, (C) Processing Speed, (D) Visuospatial Planning, (E) Executive Function & Sequencing, (F) Working Memory Load, and (G) Attention & Inhibition.

The findings also show that handwriting can function as a natural, low-effort modality for implicit cognitive assessment. In HCI, this supports the design of unobtrusive screening tools embedded in routine digital interactions. Future work should validate the framework on larger and more diverse datasets, include longitudinal analysis, and combine handwriting with other interaction modalities to improve robustness and practical use.

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