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Differences in Drawing Structure Between Parkinson's Disease and Age-Matched Controls: A Computational Image Analysis Approach

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Statement on the Use of AI-Assisted ToolsAI-assisted tools were used in a supportive capacity. These included ChatGPT (OpenAI; versions GPT-4o and GPT-5), DeepL, and Google Gemini, used between 02/2025 and 02/2026.

These tools were primarily employed for:

- Linguistic and stylistic revision (e.g. refinement of wording, grammar and clarity),
- structuring of individual sections,
- clarification of methodological and conceptual questions
- formal proofreading

All AI-generated suggestions were independently reviewed, critically evaluated, and revised by the author. All scientific content, interpretations, and conclusions are based on the author's own academic work and are supported by appropriate scholarly sources where required. The final version of this thesis was written and compiled independently.

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1. Introduction

Parkinson's disease (PD) is one of the most common and fastest-growing neurodegenerative disorders worldwide (Dorsey et al., 2018; Luo et al., 2025). Recent estimates from the Global Burden of Disease project indicate that approximately 11.8 million individuals were living with PD in 2021, with prevalence projected to more than double by 2050, primarily driven by population ageing and population growth (Luo et al., 2025; Su et al., 2025). Meta-analytic evidence further confirms a steady increase in global prevalence over the past four decades, with current pooled estimates suggesting approximately 1.5 cases per 1,000 individuals worldwide (Zhu et al., 2024). Consistent with this trend, epidemiological studies from high-income countries suggest that lifetime risk of PD may approach 6-7%, particularly among men (Wanneveich et al., 2018), aligning with recent global projections indicating a rapidly increasing population-level burden (Su et al., 2025; Luo et al., 2025).

Although PD predominantly affects older adults, a substantial number of individuals are diagnosed before the age of 50, underscoring its broader social, psychological, and economic impact beyond late life (Shen et al., 2025). This broader age range highlights that PD affects individuals during active stages of personal, professional, and creative life, reinforcing the need to understand its consequences not only in terms of survival and symptom management but also in relation to identity, autonomy, and adaptation (Charmaz, 1983; Gretton & Ffytche, 2014). In addition, PD contributes a substantial and increasing share of global disability-adjusted life years (DALYs), with millions of healthy life years lost worldwide and age-standardized DALY rates continuing to rise (Luo et al., 2025).

Beyond its clinical impact, PD is associated with a substantial and rapidly growing economic burden. Recent estimates indicate that the total societal cost of PD in the United States (U.S.) alone exceeds $50 billion annually and is projected to rise sharply over the coming decades, driven by increased healthcare utilization, long-term disability, and informal caregiving demands (Yang et al., 2020). Economically, PD is costly and growing, with U.S. expenditures heavily weighted toward institutional care, despite most patients preferring alternatives (Dieleman et al., 2016; Kowal et al., 2013). This underlines the urgent need for fresh perspectives and approaches that extend beyond pharmacological treatment, including insights into how PD shapes everyday functioning, adaptation, and expressive behavior.

Together, these demographic trends highlight the urgency of understanding PD not only as an age-related disorder but also as a major and expanding public health challenge.

PD is characterized by progressive motor and non-motor symptoms that substantially impair daily functioning and quality of life (Zhao et al., 2021). Although the disease itself is not directly fatal, complications such as falls, related injuries, and cognitive decline contribute substantially to morbidity and mortality (Palma & Kaufmann, 2018; Palma & Kaufmann, 2020).

Beyond its increasing prevalence, PD is increasingly recognized as a complex and multifaceted syndrome rather than a purely motor disorder (Chaudhary et al., 2025). While motor symptoms remain a defining feature, cognitive impairments, mood disturbances, perceptual changes, autonomic dysfunction, and sleep abnormalities are now understood as integral components of the disease (Chaudhuri et al., 2006; Schapira et al., 2017; see Section 2.2. Clinical Features of Parkinson's Disease). This expanded conceptualization blurs traditional boundaries between neurology, psychiatry, and behavioral science and highlights PD as a condition that affects nearly every domain of human functioning.

PD typically emerges slowly and insidiously, with non-motor symptoms such as perceptual changes, mood disturbances, and alterations in motivation often preceding overt motor impairment by years (Noyce et al., 2012; Palma & Kaufmann, 2018; Peña-Zelayeta et al., 2025). This gradual progression requires individuals to continually adapt to subtle but accumulating changes in how they perceive, experience, and relate to their bodies and environments (Charmaz, 1983; Gretton & Ffytche, 2014). How people experience, interpret, and respond to these evolving changes might offer important insights into processes of identity, resilience, and adaptation over the course of neurodegeneration.

Within this context, artistic expression and drawing behavior have attracted growing interest as potential windows into these adaptive processes. Rather than reflecting creativity as a stable trait or ability, emerging evidence suggests that PD and its treatment may be associated with qualitative changes in motivation, engagement, and the organization of visual expression, with substantial heterogeneity across individuals (Lauring et al., 2019; Zaidel, 2013). Case reports and small-scale studies describe both increased artistic engagement in some individuals and reduced flexibility or expressivity in others, particularly in relation to dopaminergic treatment (Chatterjee et al., 2006; Kulisevsky et al., 2009). Taken together, this literature points less toward uniform enhancement or loss of creativity and more toward disease-related changes in how visual output is structured and produced.

These observations raise the possibility that PD may give rise to characteristic patterns in drawing behavior, reflecting the interaction of motor constraints, perceptual processing, and

visuospatial planning. However, systematic investigations of such patterns remain scarce. Most existing studies rely on anecdotal reports or subjective descriptions rather than quantitative or computational analyses of artistic production (Lauring et al., 2019; Pelowski et al., 2022). As a result, little is known about whether drawings produced by individuals with PD exhibit measurable differences in their low-level structural and compositional properties compared to those of healthy individuals. Little is known about whether the objective visual, structural, and compositional properties of drawings produced by individuals with PD differ from those of healthy controls. To examine how PD may influence artistic output and drawing behavior, the following sections review the clinical, cognitive, and perceptual features of PD, alongside the emerging literature on creativity and visual expression in this condition.

Addressing this gap requires objective, feature-based approaches capable of capturing subtle changes in visual expression associated with PD. Building on these considerations, the present study focuses on quantifiable image properties related to symmetry, spatial distribution, contrast, and multiscale structure (e.g. Fourier slope, Fourier sigma, 2D fractal dimension). Rather than assessing creativity as a subjective or trait-like construct, the focus lies on detecting subtle differences in the structural organization of drawings that may arise from disease-related alterations in motor control, perceptual processing, and visuospatial planning.

Such image statistics have been linked to principles of perceptual organization and visual coding in prior work (Graham & Redies, 2010; Redies, 2015) and may additionally reflect constraints in motor planning, movement amplitude, and visuospatial control relevant to PD (Bologna et al., 2020). By combining computational feature extraction with multivariate statistical and interpretable machine-learning approaches, the study aims to identify reproducible structural signatures associated with PD.

2. Theoretical Background

2.1. Overview of Parkinson's Disease

PD is a progressive neurodegenerative disorder primarily associated with the degeneration of dopaminergic neurons in the substantia nigra pars compacta, leading to dopamine depletion in the nigrostriatal pathway (Deumens et al., 2002). This disruption of basal ganglia circuitry gives rise to the cardinal motor symptoms of PD, including bradykinesia, rigidity, tremor, and postural instability (see Section 2.2; Gröger et al., 2014).

Yet PD is now understood as a multisystem disorder, in which dopaminergic loss triggers wide-ranging and sometimes unexpected downstream effects across motor, cognitive, emotional, and autonomic systems (Chaudhary et al., 2025; Peña-Zelayeta et al., 2025). A central feature is chronic neuroinflammation: microglial activation, elevated pro-inflammatory cytokines such as TNF-α and IL-1β, and activation of the complement system contribute to ongoing neuronal stress and degeneration (Alster et al., 2023; McGeer & McGeer, 2004). Increasing evidence links these inflammatory changes to mitochondrial dysfunction, oxidative stress, impaired autophagy–lysosomal pathways, and the accumulation and misfolding of α-synuclein, which forms Lewy bodies, known as the pathological hallmark of PD.

Altogether, PD emerges from the complex interplay of neurodegeneration, neuroinflammation, environmental exposures, and genetic susceptibility. These underlying processes not only drive the classic motor symptoms but also shape the non-motor, cognitive, and perceptual disturbances that characterize the disease throughout its progression.

2.2. Clinical Features of Parkinson's Disease

Symptoms generally develop slowly over years, and the severity of motor and non-motor symptoms increases as the disease progresses (Kouli et al., 2018). Before the characteristic motor symptoms emerge, PD is preceded by a lengthy prodromal phase marked by subtle non-motor changes such as hyposmia (reduced ability to smell), REM sleep behavior disorder, constipation, and mood disturbances (Grass et al., 2025). This stage can last years or even decades and reflects ongoing neurodegenerative processes before clinical diagnosis is possible (Kouli et al., 2018). There is increasing interest in this prodromal period as a potential window for therapeutic intervention, since by the time motor symptoms appear, substantial dopaminergic neuron loss has already occurred. Many current clinical trials enroll patients

within two years of diagnosis, yet even at this point the neurodegenerative burden is significant. Therefore, future disease-modifying treatments may ideally need to be initiated during the prodromal phase (Kouli et al., 2018).

Due to PD's heterogeneity, symptoms, rate of progression, and response to treatment differ widely from person to person (Kalia & Lang, 2015). This variability is particularly relevant when considering changes in complex visuomotor behaviors such as drawing and artistic production, which depend on the interaction of motor control, perceptual processing, and cognitive planning. To capture this heterogeneity, researchers have proposed several clinical subtypes of PD based on predominant motor features, age at onset, disease progression, and the presence of non-motor symptoms. One commonly used distinction differentiates between tremor-dominant and non–tremor-dominant forms of the disease (Jankovic et al., 1990). Tremor-dominant PD is typically associated with fewer axial motor deficits and a more favorable response to dopaminergic treatment, whereas non–tremor-dominant PD is characterized by akinetic–rigid symptoms, postural instability, and a higher burden of non-motor features. These subtypes differ in clinical course and prognosis and may reflect partially distinct underlying pathophysiological mechanisms (Marras & Lang, 2013).

Such subtype-related differences may have direct implications for drawing behavior. Tremor-dominant profiles may primarily affect fine motor execution and line stability, whereas akinetic–rigid and postural-instability–dominant profiles may additionally disrupt spatial planning, movement initiation, and global organization of visual output. Considering disease heterogeneity is therefore essential for understanding variability in artistic and drawing-related changes observed in PD.

As the disease advances, these symptoms increasingly coexist with complications arising from long-term levodopa therapy (Riederer et al., 2025). These include non-motor fluctuations, dyskinesias, and psychosis, all of which are more difficult to manage clinically (Iranzo et al., 2013; Noyce et al., 2012). In advanced stages, both motor and non-motor symptoms may become resistant to existing medications. Postural instability and freezing of gait can lead to falls and fractures, while dementia and hallucinations may develop in some patients, making care home placement necessary (Kouli et al., 2018).

Together, the accumulation of motor impairment, non-motor symptoms, and treatment-related complications places increasing constraints on everyday activities that rely on fine motor control, visuospatial processing, and sustained engagement—factors that are

directly relevant for understanding changes in drawing behavior and visual expression in Parkinson's disease.

2.2.1. Motor Symptoms

The cardinal motor features of PD are known as tremor, bradykinesia, rigidity, and postural instability. They are collectively referred to as parkinsonism (Abusrair et al., 2022). Tremor occurs in about 70-75% of cases (Abusrair et al., 2022; Moustafa et al., 2016). Although resting tremor is the most common type, kinetic tremors (occurring during voluntary movement) and postural tremors (affecting the ability to maintain an upright posture) are also seen (Moustafa et al., 2016). Tremors primarily affect the hands and feet, with the classic "pill-rolling" tremor being a hallmark of PD. This involves a rhythmic motion where the thumb and index finger rub together in a circular pattern at a frequency of 4–6 Hz (Abusrair et al., 2022; Sveinbjornsdottir et al., 2016).

Bradykinesia describes difficulties in motor planning, initiation, and execution, resulting in overall slowed movement with reduced amplitude that affects sequential and simultaneous motor tasks (Bologna et al., 2020). A common consequence of bradykinesia is hypomimia, characterized by reduced facial expressions (Sveinbjornsdottir, 2016). Rigidity, also called rigor, refers to a persistent stiffness and resistance to passive muscle stretching (Moustafa et al., 2016). Postural instability generally appears in the later stages, leading to impaired balance and falls, and a forward-flexed, stooped posture (Palakurthi & Burugupally, 2019).

In addition to these cardinal motor features, individuals with PD often exhibit secondary motor symptoms (Moustafa et al., 2016). Gait disturbances are particularly prominent and contribute to the classic Parkinsonian gait, marked by shuffling steps and episodic disruptions. These include festination (an involuntary quickening of steps) and sudden freezing, both of which increase fall risk (Mirelman et al., 2019; Moustafa et al., 2016). Speech is also frequently affected, with common issues including stuttering, hypophonia (soft speech), slurring, and festinating speech, which becomes increasingly rapid and difficult to understand (Moustafa et al., 2016). Handwriting often shows progressive changes, typically becoming smaller (micrographia), jagged, and irregular (Moustafa et al., 2016). Fine motor skills, such as grip strength and finger dexterity, are likewise significantly impaired.

2.2.2. Non-Motor Symptoms

Beyond motor impairment, PD is increasingly recognized as a multisystem disorder characterized by a wide range of non-motor symptoms (Chaudhary et al., 2025; Peña-Zelayeta et al., 2025). These include autonomic dysfunction, olfactory impairment, sensory disturbances, pain, sleep disorders, mood disturbances, and cognitive deficits (Culicetto et al., 2024; Hustad & Aasly, 2020; Palmeri et al., 2017). Non-motor symptoms may precede motor onset by years and often progress independently of motor severity (Peña-Zelayeta et al., 2025).

Non-motor manifestations contribute substantially to disability and are frequently reported by patients as more burdensome than motor symptoms, exerting a profound negative impact on quality of life (Noyce et al., 2012). They are also strong predictors of functional decline and admission to long-term care facilities (Noyce et al., 2012).

Autonomic Symptoms. Autonomic dysfunction constitutes a major and clinically significant subset of the non-motor symptoms of PD and is therefore discussed separately. Autonomic nervous system failures, known as dysautonomia, can manifest at any stage of PD (Palma & Kaufmann, 2018; Pfeiffer, 2020). They can be difficult to manage and significantly impact daily life (Martinez-Martin et al., 2011, Palma & Kaufmann, 2018). While nearly all individuals with PD experience cardiovascular autonomic dysfunction, only some are symptomatic (Palma & Kaufmann, 2018). A major concern is orthostatic hypotension, which is a drop in blood pressure happening when standing after sitting or lying down. This can further lead to dizziness or lightheadedness and possibly fainting and the resulting falls are linked to increase morbidity and mortality (Palma & Kaufmann, 2018; Palma & Kaufmann, 2020). Other autonomic dysfunctions are gastrointestinal problems such as chronic constipation, delayed gastric emptying with nausea, excessive salivation, and dysphagia (difficulty swallowing), all of which contribute to a decreased quality of life (Pfeiffer, 2020). Additionally, urinary incontinence, sexual dysfunction, and thermoregulatory issues, including intolerance to heat and cold as well as excessive sweating, are also common (Pfeiffer, 2020).

Sleep Disturbances. Sleep disturbances are among the most prevalent non-motor symptoms in PD, affecting up to 98% of patients (Stefani & Högl, 2020). These disturbances include insomnia, excessive daytime sleepiness, restless legs syndrome, REM sleep behavior disorder (RBD), and sleep-disordered breathing – many of which may be exacerbated by dopaminergic medication. RBD is particularly noteworthy because it can precede the onset of

motor symptoms by years or even decades, making it one of the strongest prodromal markers of PD (Bollu & Sahota, 2017).

While sleep symptoms vary across individuals, disruptions in circadian regulation appear nearly universal at some point during disease progression (Dodet et al., 2024). Such disruptions can amplify cognitive fatigue, emotional dysregulation, and attentional difficulties, thereby indirectly influencing tasks that depend on sustained focus and sensorimotor precision.

Neuropsychiatric and Cognitive Symptoms. Neuropsychiatric symptoms, including anxiety, apathy, depression, hallucinations, and impulse control disorders, occur in an estimated 40–60% of individuals with PD and may fluctuate across the course of the illness (Aarsland & Kramberger, 2015). These disturbances significantly contribute to reduced quality of life and are sometimes exacerbated or even triggered by dopaminergic medication (Aarsland & Kramberger, 2015; Weintraub & Mamikonyan, 2019).

Among these symptoms, psychosis and hallucinations represent an important subset (Fénelon et al., 2000). Visual hallucinations, which may involve static objects appearing to move or transform into living forms, are particularly common in patients receiving dopamine agonists and reflect alterations in perceptual processing. Such perceptual changes may also influence artistic experience and visual imagination, making them relevant in the context of artistic behavior.

Cognitive impairments are likewise highly prevalent and among the most debilitating non-motor manifestations of PD (Amstutz et al., 2025). Deficits can emerge years before diagnosis, often beginning with executive dysfunction, impaired attention, slowed cognitive processing, and difficulties with temporal estimation (Biundo et al., 2016; Gonzalez-Latapi et al., 2021). As the disease progresses, up to 80% of patients develop Parkinson's disease dementia within 20 years of diagnosis (Iranzo et al., 2013), highlighting the progressive nature of cognitive decline. These impairments interfere with planning, flexibility, working memory, and goal-directed behavior, all processes relevant for creative cognition.

A particularly notable behavioral complication in PD is punding, a repetitive, stereotyped, and non-goal-directed pattern of behavior strongly associated with dopaminergic overstimulation and classified within the broader group of impulse control disorders (ICDs; Ferrara & Stacy, 2008; Lhommée et al., 2014). Although relatively rare with prevalence estimates ranging from 0.3% to 14% punding is often underrecognized and can severely disrupt

daily life (Spencer et al., 2011). Common manifestations include compulsive sorting, collecting, disassembling and reassembling objects, or repetitive manipulation of tools and materials (O'Sullivan et al., 2007; Voon & Fox, 2007). Unlike obsessive–compulsive disorder, these behaviors are not typically driven by anxiety and are often experienced as ego-syntonic by the patient (Miwa, 2007).

For studies of artistic production, punding is especially relevant. Its repetitive, stereotyped nature may superficially resemble creative engagement, for example, endless reworking of a drawing or compulsive engagement with artistic materials. However, punding differs fundamentally from creativity: whereas creativity requires novelty, intentionality, and usefulness, punding is characterized by repetition, aimlessness, and a lack of overarching purpose (Fasano & Evans, 2013; Lhommée et al., 2014). Distinguishing between these phenomena is crucial, as certain behaviors that appear artistic may in fact be manifestations of dopaminergic dysregulation rather than genuine creative expression.

Overall, neuropsychiatric and cognitive symptoms in PD reflect a complex interplay between disease progression, dopaminergic treatment, and individual psychological functioning. They shape emotional well-being, perception, cognition, and behavior, domains that are directly relevant to understanding how PD may influence artistic processes and output.

Sensory Symptoms. Sensory disturbances are highly prevalent in PD, occurring in up to 90% of patients and often appearing early in the disease course (Zhu et al., 2016). These alterations encompass both somatosensory deficits—such as impaired proprioception and tactile processing—and visual–perceptual dysfunctions, reflecting disrupted sensory integration rather than isolated sensory loss (Nolano et al., 2008). Together, these sensory abnormalities contribute substantially to functional impairment and reduced quality of life in individuals with PD.

Patients frequently report nociceptive or neuropathic pain, with peripheral neuropathy affecting as many as 55% (Corrà et al., 2023; Zhu et al., 2016). Reduced proprioception and impaired integration of body position have been reported in PD and may exacerbate gait instability and postural difficulties (Konczak et al., 2009; Park et al., 2015).

Hyposmia or anosmia is one of the earliest and most consistent sensory markers of PD, often preceding motor symptoms by years (Zhu et al., 2016). Loss of smell has diagnostic value and reflects early involvement of olfactory pathways in α-synuclein pathology.

Visual symptoms are particularly relevant for understanding artistic production, as they affect how patients perceive colors, contrast, spatial relationships, and movement. Common visual disturbances include (Weil et al., 2016):

- Reduced visual acuity and contrast sensitivity
- Impaired color discrimination, especially along the blue–yellow axis
- Deficits in eye coordination and saccadic control
- Distortions in spatial orientation and depth perception
- Difficulties in reading
- Double vision
- Facial and emotional recognition deficits

Visual hallucinations may also occur, especially in later stages or following dopaminergic treatment (Muller et al., 2014). Such perceptual alterations not only affect daily functioning but may influence artistic experience, drawing accuracy, and interpretation of visual stimuli, linking perception to artistic output.

2.3. Diagnosis

The clinical diagnosis of PD is primarily based on the presence of bradykinesia in combination with either resting tremor or rigidity, typically with an asymmetric onset and a positive response to levodopa (Pradeep & Kamalakannan, 2024; Williams-Gray & Worth, 2016). A definitive confirmation of PD has historically required post-mortem detection of Lewy bodies containing misfolded α-synuclein (Deumens et al., 2002). Recent advances in imaging and fluid biomarkers now allow for a probable diagnosis during life, although post-mortem confirmation remains the research gold standard (Zarkali et al., 2024).

Early diagnosis remains challenging because initial symptoms are often subtle non-specific or dominated by non-motor changes. Prodromal features including hyposmia, constipation, depression, and REM sleep behavior disorder can appear 10–15 years before the onset of motor signs (Postuma et al., 2012; Schrag et al., 2015). This prodromal period is increasingly recognized as a critical window for identifying individuals at risk and for initiating potential disease-modifying interventions before substantial dopaminergic loss has occurred.

To assist early detection, biomarkers such as olfactory testing, RBD screening, and dopaminergic imaging (e.g., DaTscan) can support the diagnostic process, although they cannot confirm PD independently (Brücke & Brücke, 2022; Postuma et al., 2012). Yet no single test is sufficient for diagnosis, and accuracy still relies heavily on expert clinical judgment. Differential diagnosis of PD includes atypical parkinsonian syndromes — such as multiple system atrophy and progressive supranuclear palsy — as well as essential tremor and drug-induced parkinsonism, all of which require careful clinical evaluation to distinguish from idiopathic PD (Shin & Hong, 2022).

2.4. Treatment

PD treatment primarily targets symptom reduction and quality of life, as no available therapy has been shown to halt or reverse disease progression (Armstrong & Okun, 2020).

2.4.1. Pharmacological Treatment

Dopaminergic medication remains the cornerstone of PD treatment.

- Levodopa, combined with carbidopa, is the most effective therapy for improving bradykinesia and rigidity and is the first-line treatment for functional impairment (Armstrong & Okun, 2020).
- Dopamine agonists (e.g., pramipexole, ropinirole) activate dopamine receptors directly and may be used as monotherapy in early PD or in combination therapy. However, they carry a higher risk of neuropsychiatric effects, including impulsivity and creativity enhancement (Connolly & Lang, 2014; Seppi et al., 2011).
- Other pharmacological options include MAO-B inhibitors, COMT inhibitors, adenosine A2A antagonists, amantadine, and anticholinergics (Höllerhage et al., 2024).

The timing and dosing of dopaminergic medication is critical in PD management. Many patients experience motor fluctuations, such as “wearing off” phenomena in which symptoms re-emerge before the next dose, or dyskinesia that typically occur at peak medication levels (Masood & Jimenez-Shahed, 2023). Treatment therefore requires continuous adjustment to balance symptom control and side effects.

In addition to motor complications, dopaminergic therapy—particularly dopamine agonists—may induce neuropsychiatric side effects, including impulse control disorders such

as pathological gambling, compulsive shopping, hypersexuality, or binge eating (Moore et al., 2014). These behavioral changes underscore that dopamine replacement affects not only motor circuits but also broader cortico-striatal systems involved in motivation and reward processing.

At a neurobiological level, dopamine modulates distributed cortico-striatal networks that regulate movement initiation, motor scaling, action selection, and cognitive flexibility (Obeso et al., 2008; MacDonald & Monchi, 2011). Degeneration of nigrostriatal pathways disrupts movement amplitude and velocity, as well as sensorimotor integration and effort regulation (Bologna et al., 2020; Moustafa et al., 2016). Because dopaminergic therapy influences both dorsal motor and ventral associative circuits, its effects extend beyond pure motor restoration to processes related to engagement and goal-directed behavior. These dynamics are particularly relevant for complex visuomotor activities such as drawing, which require coordinated motor execution, spatial planning, and sustained perceptual monitoring.

2.4.2. Surgical Therapies

When medication adjustments fail to adequately control symptoms, deep brain stimulation (DBS) may be considered. DBS most commonly targets the subthalamic nucleus or globus pallidus internus, improving tremor, rigidity, bradykinesia, “wearing off”, and medication-induced dyskinesias (Armstrong & Okun, 2020).

Other procedures include:

- Focused ultrasound for unilateral tremor (Armstrong & Okun, 2020; Dahmani et al., 2023) and
- Levodopa–carbidopa intestinal gel infusion as continuous dopaminergic delivery (Armstrong & Okun, 2020; Odin & Rosqvist, 2023).

All surgical options require multidisciplinary evaluation. Importantly, these treatments do not address non-motor symptoms such as cognitive impairment or psychological difficulties.

2.4.3. Rehabilitative Therapy and Non-Pharmacological Therapies

As soon as PD is diagnosed, rehabilitative therapy should be introduced and continued throughout the disease course (Kouli et al., 2018). Exercise programs including stretching, resistance training, and aerobic activity are consistently associated with improved motor function and quality of life (Armstrong & Okun, 2020). Physical, occupational, and speech therapy further address gait, fine motor skills, and communication of swallowing difficulties (Armstrong & Okun, 2020). High-intensity training, cueing techniques, dance therapy, and mindfulness-based interventions have shown promising benefits, reflecting the importance of multimodal behavioral approaches (Barnish & Barran, 2020; Li et al., 2022; Lihala et al., 2021; Wang et al., 2021; Wang et al., 2022).

Since PD affects not only motor function but also mood, cognition, and quality of life, psychological interventions such as cognitive-behavioral therapy (CBT) for anxiety or depression may also be beneficial (Wu et al., 2024).

2.4.4. Psychosocial and Supportive Interventions

While pharmacological and surgical treatments address the motor and some non-motor manifestations of PD, psychosocial and supportive interventions play an essential role in maintaining quality of life, emotional well-being, and functional independence. Because PD affects identity, autonomy, interpersonal relationships, and coping processes, psychological support is considered a core component of comprehensive care (Charmaz, 1983; Gretton & Ffytche, 2014).

Psychological Therapies. CBT has demonstrated effectiveness in reducing anxiety, depression, and sleep disturbances in PD (Alnajjar et al., 2024; Berardelli et al., 2015). CBT can also support coping with chronic illness, adjustment to disability, and management of apathy or low motivation. These symptoms are all strongly linked to dopaminergic dysfunction.

Mindfulness-based interventions have been associated with improvements in emotional regulation, stress, quality of life, and perceived motor symptoms (de Vibe et al., 2017). These approaches may modulate attentional processes and help patients adapt to fluctuating symptom patterns.

Psychoeducation and Self-Management. Structured psychoeducational programs improve patients' understanding of disease progression, treatment principles, medication timing, and self-care strategies (Hellqvist et al., 2020; Tennigkeit et al., 2020). Such programs reduce helplessness and enhance a sense of control, which is psychologically important given PD's unpredictable trajectory. Self-management interventions, including exercise routines, goal setting, and daily rhythm planning, have shown benefits for functional independence and self-efficacy (Milne-Ives et al., 2022).

Social Support and Caregiver Interventions. The psychosocial impact of PD extends to partners, spouses, and caregivers. Caregiver burden is strongly associated with patient neuropsychiatric symptoms, cognitive decline, and motor fluctuations (Wu et al., 2025). Support groups, respite care, and caregiver education programs can reduce psychological strain and promote healthier family dynamics (Longacre et al., 2025).

Peer support groups offer emotional validation, reduce loneliness, and provide practical coping strategies. Social connectedness is a predictor of better psychological adjustment and slower functional decline (Kotwal et al., 2021).

Multidisciplinary Rehabilitation. Optimal psychosocial care is achieved through multidisciplinary teams integrating neurologists, psychologists, physiotherapists, speech therapists, and social workers. Multidisciplinary models improve quality of life, mood, and caregiver satisfaction (Tan et al., 2014), further emphasizing that PD management is not purely biomedical but also deeply psychological and social.

2.4.5. Classification and Assessment of Severity

To understand how symptom severity and disease progression may influence artistic production, it is essential to consider how PD is clinically classified and staged. This section outlines the distinction between idiopathic and atypical parkinsonism, reviews major clinical and functional staging systems, and considers how these frameworks inform the interpretation of drawing behavior and visual expression in PD.

2.4.6. Idiopathic vs. Atypical Parkinsonism

For research on artistic production, distinguishing idiopathic PD from atypical parkinsonian syndromes is essential. Atypical conditions such as progressive supranuclear

palsy, multiple system atrophy, corticobasal degeneration, and dementia with Lewy bodies are characterized by earlier and more severe impairments in visuospatial abilities, executive functioning, postural control, and gait stability (Armstrong & McFarland, 2019; Levin et al., 2016). These domains are directly implicated in drawing, composition, and visual planning, suggesting that atypical parkinsonism would produce qualitatively different patterns of artistic output compared to idiopathic PD. For this reason, studies examining drawing behavior or creativity in PD typically exclude atypical parkinsonian syndromes to ensure that observed changes can be attributed to disease-related motor and perceptual alterations rather than more global cognitive or visuospatial breakdown.

2.4.7. Clinical Staging Systems

The Unified Parkinson's Disease Rating Scale (UPDRS; Fahn & Elton, 1987) and its revised version, the Movement Disorder Society–sponsored revision (MDS-UPDRS; Goetz et al., 2008) are the most widely used clinical instruments for evaluating PD symptoms. The MDS-UPDRS consists of four parts assessing different domains of impairment:

- Part I – Non-Motor Experiences of Daily Living (e.g., cognitive impairment, mood, apathy).
- Part II – Motor Experiences of Daily Living (e.g., speech, feeding, handwriting).
- Part III – Motor Examination (e.g., facial expression, rigidity, bradykinesia, tremor).
- Part IV – Motor Complications (e.g., dyskinesias, motor fluctuations).

Each item is rated from 0 (normal) to 4 (severe), allowing clinicians to quantify both motor and non-motor symptom severity. For studies of drawing and artistic behavior, UPDRS scores provide a structured way to contextualize how motor constraints (e.g., bradykinesia, tremor), affective symptoms (e.g., apathy), and cognitive changes may differentially influence visual output, line quality, and compositional complexity.

2.4.8. Hoehn and Yahr Staging

The Hoehn and Yahr scale (HY; Goetz et al., 2004; Hoehn & Yahr, 1967) provides a simpler classification of PD progression based on motor symptom severity and functional independence:

- Stage I: Unilateral involvement only, with minimal or no functional impairment.

- Stage II: Bilateral or midline involvement without loss of balance.
- Stage III: Postural instability with preserved independence; mild-to-moderate disability.
- Stage IV: Severe disability; able to walk or stand unassisted but functionally limited.
- Stage V: Bedridden or wheelchair-bound without assistance.

In the context of artistic production, HY staging helps situate observed drawing characteristics within a broader trajectory of motor decline. Earlier stages may allow relatively preserved visuomotor coordination, whereas later stages are associated with reduced gesture amplitude, impaired spatial organization, and increased reliance on compensatory strategies. Some reports further suggest non-linear patterns, with increased artistic engagement or stylistic change emerging in early disease stages before declining as motor and cognitive symptoms worsen (Lauring et al., 2019).

2.4.9. Braak Staging

From a neuropathological perspective, Braak staging describes the progression of Lewy body pathology within the brain (Braak et al., 2003):

- Stages I–II: lower brainstem and olfactory areas
- Stages III–IV: midbrain and limbic regions
- Stages V–VI: widespread neocortex

Although Braak staging is primarily applied in postmortem and imaging studies rather than behavioral research, it provides a theoretical framework for linking symptom emergence to underlying neural degeneration (Cimmino et al., 2025; Hawkes et al., 2010). Importantly, this framework suggests that changes in motivation, affect, and perceptual processing may precede overt motor impairment, offering a neurobiological basis for early alterations in drawing behavior and visual expression.

2.4.10. Relevance to Art Assessment

For studies of artistic production, these classification systems provide essential context for interpreting stylistic and aesthetic differences among PD patients. Integrating disease stage

data can help determine whether changes in artistic output, such as alterations in complexity, structure, or expressivity, may reflect motor constraints, cognitive shifts, or medication-related modulation of motivation and reward processing. In this way, clinical classification contributes directly to understanding the neuroaesthetic mechanisms underlying creativity and visual expression in PD.

2.5. Empirical Evidence for Artistic and Structural Change in Parkinson's Disease

2.5.1. Early Observations: Creative Surges and Dopaminergic Modulation

Interest in the relationship between PD and artistic expression initially emerged from anecdotal case reports and small observational studies. Many of these reports documented the emergence or intensification of artistic behavior following the initiation of dopaminergic therapy, particularly dopamine agonists (Chacko et al., 2019; Chatterjee et al., 2006; López-Pousa et al., 2012; Schrag & Trimble, 2001). Patients reported engaging in painting, writing, sculpting, or in other creative practices with unusual intensity, persistence, or productivity, often describing these activities as intrinsically rewarding or even compulsive. In several cases, these creative surges diminished after medication reduction or following subthalamic nucleus deep brain stimulation (STN-DBS), suggesting a role for dopaminergic tone in modulating motivation and expressive behavior (Kulisevsky et al., 2009; Lhommée et al., 2014).

Classic clinical narratives further popularized these observations. Sacks (1985, 1995) described patients who developed new or intensified artistic and musical abilities in the context of neurological disease or treatment. Such accounts were striking given the relative rarity of large post-adolescent shifts in artistic engagement or style in the general population (Barbot & Tinio, 2015). These cases suggested that neurological and pharmacological changes may not merely degrade function, but in some instances alter motivational and expressive systems in unexpected ways.

Despite their influence, early case reports were methodologically limited. Creativity was typically assessed through self-report, caregiver testimony, or qualitative description, and premorbid baselines were rarely available. Sample sizes were small, outcome measures varied widely, and few studies employed standardized psychometric tools or objective analysis of artistic output (Walker et al., 2006). However, these accounts primarily concern motivational

and top-down aspects of creativity rather than compositional or structural properties of artistic output.

Thus, early observations established the phenomenon of artistic change in PD but left open fundamental questions regarding nature, consistency, and underlying mechanisms of these changes.

2.5.2. Heterogeneity of Creative Outcomes

Subsequent surveys and experimental studies revealed substantial heterogeneity in creative outcomes among individuals with PD. Rather than demonstrating uniform enhancement or decline, findings suggest variable and sometimes contradictory patterns across patients and study designs. Table 1 provides an overview of key empirical investigations examining artistic and creative changes in PD, summarizing study designs, sample characteristics, operationalizations of creativity or artistic output, principal findings, and methodological limitations. Conceptualizations of “creativity” vary widely, and outcome measures differ substantially across studies.

Notably, few studies have examined the structural properties of visual output using objective, multivariate image-based methods (e.g., Forsythe et al., 2017; Lauring et al., 2019; Pelowski et al., 2022). This gap motivates the present computational approach. In a large survey of 793 patients, 41% reported changes in creativity after diagnosis: 12% described increases, 22% decreases, and 7% fluctuations over time (Spee et al., 2025). Increases were associated with dopamine agonist use and longer disease duration, whereas older age and premorbid artistic engagement predicted decreases. Similarly, Joutsa et al. (2012) found that 19.3% of patients reported enhanced artistic creativity following diagnosis, with a subset attributing this directly to dopaminergic therapy. These findings underscore that creative change in PD is neither uniform nor inevitable but varies across individuals.

Experimental studies using psychometric creativity tasks have likewise produced mixed results. Some investigations reported reduced flexibility or originality in divergent thinking tasks among medicated patients (Heldmann et al., 2024; Salvi et al., 2021), whereas others observed enhanced originality and flexibility under dopaminergic treatment, particularly in patients without marked executive dysfunction (Faust-Socher et al., 2014). Reviews of the literature suggest that dopaminergic stimulation may amplify preexisting tendencies rather than generate creativity de novo, with individual differences in premorbid artistic inclination,

cognitive reserve, and neural integrity playing moderating roles (Canesi et al., 2016; Marafioti et al., 2025).

However, most of this literature conceptualizes creativity as a high-level construct involving motivation, originality, novelty-seeking, or divergent thinking. Such measures primarily assess top-down cognitive and affective dimensions of creative behavior. Far less attention has been devoted to the low-level structural properties of visual production — that is, how drawings or artworks are spatially organized, composed, and executed.

This distinction is particularly important in PD. Alterations in motor control, visuospatial processing, perceptual integration, and reward modulation may influence not only whether individuals feel motivated to create, but also how visual output is structured at the level of line, balance, symmetry, and complexity. Yet systematic, multivariate analyses of these structural features remain scarce. Consequently, it remains unclear whether PD is associated with reproducible patterns, or artistic signatures, in the formal properties of drawings.

The need to move beyond subjective creativity ratings toward objective, feature-based characterization of visual output therefore represents a critical gap in the literature and forms the foundation for the present study.

Table 1

Overview of Key Empirical Studies

Study	Study Type	Sample Size	Creativity Measure	Medication Status	Main Findings	Key Limitations
Chatterjee et al. (2006)	Case study	PD: 1 HC: 0	Qualitative case description; self-report; visual inspection	Dopaminergic therapy (implied)	Increased artistic output and stylistic change (abstraction, repetition, urgency)	Single case; no objective or standardized assessment
López-Pousa et al. (2012)	Longitudinal case report	PD: 1 HC: 0	Qualitative longitudinal artwork description; self-report	Dopaminergic therapy (multiple agents over time)	Increased artistic engagement and stylistic evolution over disease course	Single case; no standardized or objective creativity measures
Spee et al. (2025)	Survey study	PD: 793 HC: 0	Self-report questionnaire	DA vs. levodopa/no medication	41% reported creativity changes; increases more common with DA and premorbid creative engagement	Self-report only; no objective or product-based assessment
Salvi et al. (2021)	Experimental study	PD: 13 HC: 26	Psychometric tasks (AUT, CRA, Rebus)	ON vs. OFF dopaminergic therapy	DRT did not enhance creativity; PD patients on medication showed reduced flexibility and poorer convergent thinking	Task-based measures, no analysis of artistic products
Faust-Socher et al. (2014)	Experimental study	PD: 27 HC: 27	Psychometric tasks (TACT, RAT, CNM)	Dopaminergic treatment (DA ± levodopa)	PD patients showed enhanced divergent creativity compared to controls	Task-based measures; no analysis of artistic production
Marafioti et al. (2025)	Scoping review	7 studies	Heterogeneous (case reports, surveys, tasks)	Dopaminergic therapy	Dopaminergic therapy may amplify pre-existing creativity but does not consistently induce it	Few studies; high methodological heterogeneity

2.5.3. From Creative Drive to Visual Structure

While motivational and cognitive models of creativity are informative, artistic production also depends on low-level perceptual and motor processes. Drawing requires visuospatial planning, motor scaling, spatial organization, and the continuous integration of sensory feedback (Chatterjee & Vartanian, 2014). PD affects precisely these systems, through bradykinesia, reduced movement amplitude, impaired motor scaling, and alterations in visuospatial processing (Bologna et al., 2020; Weil et al., 2016).

Thus, even in the absence of changes in creative intent or motivation, PD may alter how visual material is physically structured and executed. This distinction between creative drive and visual structure is crucial: a person may feel equally creative, yet produce drawings that differ systematically in spatial organization, scale, density, or multiscale complexity.

2.5.4. Motor and Graphomotor Changes Relevant to Artistic Output

A more direct precedent for structural change in produced visual output comes from research on handwriting in PD. Handwriting impairments are among the earliest and most reliable motor manifestations of PD (Becker et al., 2002; Letanneux et al., 2014; McLennan et al., 1972; Ponsen et al., 2008; Saunders-Pullman et al., 2008) and have been proposed as sensitive physiological biomarkers for early detection (Rosenblum et al., 2013). Handwriting deficits have demonstrated high diagnostic sensitivity in distinguishing PD patients from controls (Duarte et al., 1995; Mutch et al., 1991).

Micrographia (progressive reduction in writing size) remains a hallmark feature of Parkinsonian dysgraphia. However, contemporary research emphasizes that handwriting alterations in PD cannot be reduced to size reduction alone (Letannaux et al., 2014). Rather comprehensive kinematic analyses reveal alterations in movement velocity, fluency, acceleration profiles, scaling, and automaticity (Caligiuri et al., 2006; Contreras-Vidal et al., 1998; Klawans, 1986; Lange et al., 2006; Lewitt, 1983; Margolin & Wing, 1983; McLennan et al., 1972; Ondo & Satija, 2007; Poluha et al., 1998; Tucha et al., 2006). These impairments likely reflect the combined effects of bradykinesia, rigidity, tremor, and freezing phenomena on graphomotor dysfunction.

Digitized handwriting studies using graphic tablets have demonstrated that low-level movement parameters can sensitively track disease severity and dopaminergic modulation

(Thomas et al., 2017). Several authors argue that isolating motor contributions requires minimizing higher-order linguistic and cognitive demands and instead focus on employing simple, well-controlled graphomotor tasks (Caligiuri et al., 2006; Contreras-Vidal et al., 1998; Poluha et al., 1998). This methodological principle is directly relevant for the study of drawing behavior. If low-level motor disturbances alter the kinematic structure of handwriting, it follows that similar constraints may influence the spatial and structural organization of other forms of visual production.

In addition to handwriting, spiral tracing tasks have been widely used to quantify fine motor control in PD (Aldhyani et al., 2024; San Luciano et al., 2016; Wang et al., 2025). In these tasks, participants trace a pre-defined Archimedean spiral, allowing precise measurement of movement smoothness, tremor amplitude, velocity fluctuations, path deviation, and spatial regularity. Deviations from the ideal spiral trajectory, such as irregular curvature, oscillatory tremor artifacts, or progressive reduction in amplitude provide sensitive and objective markers of motor dysfunction (Yoon & Ahn, 2023).

Spiral tracing tasks move beyond purely temporal or kinematic measures and directly quantify alterations in geometric form (Jenei et al., 2025). Even in a highly constrained task with a fixed spatial template, individuals with PD exhibit systematic distortions in spatial layout and curvature. These findings demonstrate that Parkinsonian motor pathology does not merely slow movement or increase variability but can measurably alter the spatial structure of produced lines. In other words, motor dysfunction becomes visible in the geometry of the trace itself.

This insight is particularly relevant for the study of drawing behavior. If motor constraints can distort the geometric organization of a simple spiral, it is plausible that similar constraints influence more complex and open-ended forms of visual production. However, unlike spiral tracing, free drawing introduces additional demands on visuospatial planning, compositional organization, and perceptual monitoring. Whether Parkinson's-related motor pathology extends beyond simple template-following tasks to affect the structural properties of drawings remains largely unexplored.

Together, findings from handwriting and spiral tracing research indicate that PD produces reliable and quantifiable alterations in structured visuomotor output. In both writing and spiral tracing, motor impairments manifest not only as slowed movement but as measurable changes in the spatial form and geometric properties of produced traces.

However, these paradigms typically involve either overlearned symbolic movements such as writing (Palmis et al., 2017) or highly constrained templates such as spiral tracing (San Luciano et al., 2016; Wang et al., 2025).

It therefore remains an open question whether similar structural alterations are observable in less constrained forms of visual production, such as free drawing. Drawing requires continuous coordination of motor execution with spatial placement and form construction across the page. Extending graphomotor research to drawing thus allows examination of whether Parkinson's-related motor constraints are reflected in the broader structural organization of produced images.

2.5.5. Perceptual and Visuospatial Contributions to Visual Production

Beyond motor execution, PD is associated with alterations in perceptual and visuospatial processing that may influence visual production. Drawing does not depend solely on motor output; it also relies on intact visual encoding, spatial judgment, and perceptual organization. In healthy adults, contrast sensitivity, color discrimination, spatial orientation, and configural processing support accurate perception of form, balance, and proportional relationships—capacities directly relevant for compositional decisions in drawing (Chatterjee & Vartanian, 2014). Within neuroaesthetic frameworks, perceptual systems interact with reward and semantic networks in shaping both the production and evaluation of visual art (Ishizu & Zeki, 2011; Kawabata & Zeki, 2004).

In PD, several aspects of visual perception are frequently altered. Reduced contrast sensitivity, particularly at intermediate and high spatial frequencies, is well documented (Brown et al., 2025; Bulens et al., 1987; Hutton et al., 1993; Repka et al., 1996; van der Lijn et al., 2022; van der Lijn et a., 2023). Such deficits may impair contour detection and fine-detail representation, potentially influencing the density, clarity, or multiscale structure of drawings. Color discrimination can also be affected, with slowed chromatic processing and progressive difficulty distinguishing hues (Büttner et al., 1993; Price et al., 1992). While dopaminergic medication may partially improve contrast sensitivity, color perception often shows more limited recovery (Büttner et al., 2000; Dalrymple-Alford et al., 2010).

Beyond basic visual functions, higher-order visuospatial functions may also be disrupted. Impairments in spatial orientation, verticality perception, and configural or holistic processing, have been reported in PD (Davidsdottir et al., 2005; Sprengelmeyer et al., 2003;

Weil et al., 2016). Such alterations could influence global spatial layout, symmetry, proportionality, and balance in visual compositions. Visual hallucinations in later stages of PD further illustrate disturbances in perceptual integration and top-down modulation (Fénelon et al., 2000; Ffytche, 2005), highlighting the broader involvement of perceptual networks in the disease.

Taken together, PD affects not only the motor execution of drawing but also the perceptual and spatial systems that guide visual organization. These combined influences provide a plausible mechanistic basis for structural alterations in drawing behavior. Rather than reflecting changes in creativity per se, differences in visual output may arise from altered contrast processing, spatial integration, and visuospatial planning, factors that can be captured through objective image-based measures of symmetry, spatial distribution, and multiscale structure.

2.5.6. Toward Objective, Computational Characterization of Drawing Structure

In response to the limitations of subjective creativity assessments, recent research has begun to shift toward computational analysis of visual properties. Methods such as fractal dimension analysis and image-based statistical modeling have been used to quantify stylistic characteristics in artworks produced by neurological populations (Forsythe et al., 2017; Lauring et al., 2019; Pelowski et al., 2022). These approaches allow examination of measurable properties such as complexity, multiscale structure, and spatial organization, independent of subjective evaluations of creativity.

However, existing computational studies remain scarce and often focus on small samples, single-case material, or isolated features. To date, there has been no systematic, multivariate examination of low-level structural drawing features in PD that integrates motor-relevant, perceptual, and spatial image properties within a unified analytical framework.

Given robust evidence that PD alters handwriting kinematics, motor scaling, perceptual sensitivity, and visuospatial organization, it is plausible that these alterations may manifest as reproducible patterns in drawing structure. Identifying such patterns would move the field beyond anecdotal reports toward an objective characterization of potential “artistic signatures” of Parkinson’s disease.

2.5.7. Present Study: From Graphomotor Evidence to Image-Based Analysis

Building on established findings from handwriting research and emerging computational approaches in neuroaesthetics, the present study investigates whether drawings produced by individuals with PD differ systematically from those of age-matched healthy controls in their structural properties.

Rather than evaluating creativity as a trait or subjective construct, the study focuses on quantifiable image features related to contrast, symmetry, spatial distribution, multiscale structure, and frequency-domain characteristics. These metrics provide a reproducible framework for capturing subtle alterations in visual production that may reflect disease-related changes in motor control, perceptual processing, and visuospatial planning.

By combining standardized computational feature extraction with multivariate statistical and interpretable machine-learning methods, the study aims to determine whether PD is associated with consistent and measurable changes in drawing structure at the level of image organization. In doing so, it moves beyond anecdotal and self-report accounts toward a systematic characterization of potential visual signatures of PD.

3. Methods

3.1. Overview

The present study employed a multi-stage design combining behavioral data collection, computational image analysis, and statistical modeling to examine disease-related differences in drawing behavior in PD. Data were drawn from three participant groups (Parkinson's disease patients, age-matched healthy controls, and younger student controls), each of whom completed drawing tasks under standardized conditions.

For the purpose of the present thesis, analyses focused on a cue-based paper drawing task in which each participant produced three drawings, yielding repeated observations per individual. Additional tablet-based drawing and spiral tracing tasks were collected as part of a broader research protocol but are not analyzed here.

Drawings were digitalized and analyzed using the Aesthetics Toolbox (Redies et al., 2025) to extract a standardized set of low-level visual features capturing contrast, symmetry, spatial organization, and multiscale structure. These features formed the basis for multivariate statistical analyses conducted by the author. In a complementary step, supervised machine-learning models were implemented in collaboration with an experienced researcher to assess predictive separability between groups. The following sections describe participants, tasks, screening procedures, and analytic methods in detail.

3.2. Participants

A total of 188 individuals participated in this study: 62 patients diagnosed with idiopathic Parkinson's disease (PD), 69 healthy age-matched controls (HC), and 57 healthy student controls (SC). All participants provided written informed consent before participation. Testing took place individually in a quiet, well-lit room. Participants were seated across from the assessor at a table. Participation was voluntary, and subjects could withdraw at any time without consequence. Data collection in Vienna was approved by the University of Vienna Ethics Committee. The data collection of the PD group was approved by Radboud UMC ethics board.

3.2.1. Parkinson's Disease Group

Data for the PD group were obtained from baseline assessments of a previous randomized controlled trial titled *"Artistic Creativity & Anxiety in Parkinson's Disease"* conducted at the Expertise Centre for Parkinson and Movement Disorders, Radboud University Medical Center, Nijmegen, the Netherlands.

- Inclusion criteria: idiopathic PD diagnosis, age ≥ 18 years, willingness to participate, and adequate global cognition (MoCA > 18; Katz et al., 2021).
- Exclusion criteria: Hoehn & Yahr stage 5 (even in the best ON state), severe cognitive impairment (MoCA < 18), requirement for full-time nursing care, or lack of written informed consent.
- The final sample consisted of 62 participants (41 female, 21 male; M_{age} = 65.5, SD = 9.38).

3.2.2. Healthy Age-Matched Control Group

Data for the HC were collected by the author between July and August 2025 using the same standardized drawing protocol as applied to the PD sample.

- Inclusion criteria: age ≥ 37 years (since the youngest person in the PD group was 37 years of age), MoCA > 18, no history of neurological or psychiatric disorder, and willingness to complete all drawing tasks.
- Exclusion criteria: BFAS ≥ 3, since scores at or above this validated cut-off indicate Parkinson-related motor symptoms warranting exclusion (see Section 3.3.2 for details; York et al., 2020); current or past neurological or psychiatric conditions; essential tremor; or lack of informed consent. Four participants were excluded based on screening results. The final HC sample comprised 69 individuals matched to the PD group for age and approximately gender.

3.2.3. Student Control Group

Data for the SC group were obtained from Pelowski et al. (2019), conducted at the University of Vienna, Austria. This group served as a younger, non-clinical comparison cohort to examine potential age-related influences on drawing performance. The goal of including this group was to compare the PD and age-matched control samples with a younger, non-clinical cohort with minimal art-making experience, especially to see if there is an age effect. The dataset comprised 57 participants (48 female, M_{age} = 21.3, SD = 3.9, range: 18-36 years). All participants were undergraduate students who met the following criteria:

- No formal or frequent experience in art making or design-design–related hobbies (verified through a post-study questionnaire),
- No history of neurological or psychiatric disorders,
- Voluntary participation, with most receiving course credit.

From the broader protocol, the cued art-making task was used for the present analyses.

3.3. Questionnaire and Screening Instruments

3.3.1. Demographic Questionnaire

Participants in the age-matched control group completed a demographic questionnaire assessing age, gender, handedness, and tablet-use habits, as well as current medication and any neurological or psychiatric diagnoses. In addition, this group provided self-reports on artistic experience (e.g. whether they have received any training or education in art-making) and imaginative tendencies (Feng et al., 2017). These variables were included to characterize potential sources of variation in drawing performance within the HC group.

For the PD group and the SC, only age and gender were available because their data had been collected prior to the planning of the present study and under different protocol requirements.

3.3.2. Baylor Functional Assessment Scale (BFAS)

The Baylor Functional Assessment Scale (BFAS) is a self-administered screening instrument designed to differentiate individuals with PD from those with other movement disorders and from healthy controls (York et al., 2020). The scale assesses core motor symptoms characteristic of PD, including bradykinesia, tremor, rigidity, postural abnormalities, handwriting difficulties, speech impairments, gait disturbances, balance problems, and challenges in ambulation (Jankovic, 2008).

A cut-off score of 3 has been validated as an effective threshold for identifying PD. This cut-off yields a sensitivity of 85.7%, specificity of 87.7%, a negative predictive value (NPV) of 93.8%, and a negative likelihood ratio (NLR) of 0.16, indicating strong discriminative validity. Scores below 3 strongly predict the absence of PD.

While the PD group was assessed with the MDS-UPDRS as part of their clinical care, the BFAS was used for healthy controls to efficiently screen for Parkinson-like symptoms. The MDS-UPDRS requires a trained clinician and is less suited for exclusion in non-clinical populations. In contrast, the BFAS is brief, self-administered, and validated to distinguish PD from healthy individuals, making it appropriate for research settings (York et al., 2020). Using the BFAS allowed rapid, standardized screening without requiring a full clinical assessment, ensuring that participants with undiagnosed motor symptoms or prodromal PD were excluded. This approach minimized participant burden, maintained methodological consistency, and avoided the ethical implications of performing diagnostic assessments on healthy volunteers.

Taken together, these considerations make the BFAS the most suitable tool for screening and exclusion in the present study.

3.3.3. Montreal Cognitive Assessment (MoCA)

Global cognitive functioning was assessed using the Montreal Cognitive Assessment (MoCA; Nasreddine et al., 2005), a widely used screening tool in PD research (Dalrymple-Alford et al., 2010; Marras et al., 2013). The MoCA evaluates eight cognitive domains, including memory, visuospatial skills, executive functions, attention, language, abstraction, calculation, and orientation. The standard paper-based version consists of a one-page, 30-point assessment and typically requires about 10 minutes to administer.

Tasks include short-term memory recall, visuospatial and executive items (e.g., clock drawing, cube copy, Trail Making–style alternation), phonemic fluency, naming, attention and

working-memory tasks (e.g., tapping, digit span, serial subtraction), and temporal and spatial orientation.

The MoCA was administered in accordance with standardized procedures following successful completion of the official MoCA Training and Certification Program, which is required to ensure proper administration and maintain the test's validity. The MoCA demonstrates good psychometric properties, including high test–retest reliability, strong internal consistency, and established content validity through correlations with the MMSE (Nasreddine et al., 2005).

In the present study, the MoCA was used to ensure that healthy control participants did not exhibit clinically relevant cognitive impairment that could confound drawing performance, confirming that they were cognitively healthy. Neurodegenerative changes, such as those seen in dementia, can potentially influence creative abilities (Gretton & Ffytche, 2014; Pelowski et al., 2022).

3.4. Artistic Tasks

Participants completed three drawing-based tasks designed to assess artistic production under standardized conditions. All tasks were administered in a quiet, moderately lit room, with the participants seated at a table opposite the assessor.

The present study employed controlled cue-based drawing rather than spontaneous artistic production. This design addresses limitations of prior research, which has frequently relied on retrospective self-report (e.g., Spee et al., 2025), anecdotal case material (e.g., Sacks, 1985; Chacko et al., 2019), or highly idiosyncratic artworks produced outside standardized conditions (Lauring et al., 2019; Pelowski et al., 2022). By stimulus cues, materials, drawing duration, and task instructions, the present paradigm allows structural properties of visual output to be compared across individuals in a reproducible manner.

Only the paper-based drawing task is analyzed in the present thesis. The tablet-based and spiral tracing task were collected as part of broader research purposes but are not included in the current analyses.

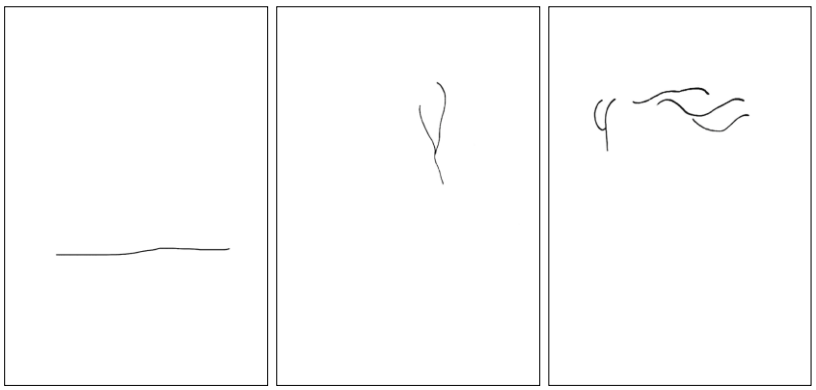
3.4.1. Creative Drawing Task (Paper)

Participants completed three cue-based creative drawings adapted from Pelowski et al. (2019). Each participant received three A4 sheets, each containing a unique black visual cue (see Figure 1).

Instructions. Participants were asked to create an original artwork inspired by the cue. They were free to interpret or use the cue in any way, draw figuratively or abstractly, and rotate the paper as needed. To encourage continuous engagement and reduce performance anxiety, participants were told that "mistakes" should be corrected creatively or incorporated into the drawing. This open-ended yet structured instruction allows for individual variation in visual production while maintaining experimental comparability across participants.

Figure 1

Visual Cues Utilized in the Cued, Drawing Task



Note. Pelowski et al., 2019; Cue 1 on the left, Cue 2 in the middle, Cue 3 on the right.

Procedure.

- Each drawing trial lasted 3 minutes.
- A verbal reminder was given after 2 minutes.
- A black Edding 400 permanent marker (1mm) was used to standardize line thickness and prevent erasing.

- Each participant produced three drawings (one per cue).

Standardizing drawing duration and materials reduces variability attributable to external factors and ensures that observed differences in image structure reflect participant-related rather than task-related variation.

Cue Order Counterbalancing. To control for potential order effects, cue presentation was fully counterbalanced across participants. With three cues, six possible orders exist (3!), and participants were assigned to these sequences as evenly as possible. This procedure ensured that each cue appeared equally often in each serial position, thereby eliminating systematic bias due to presentation order.

3.4.2. Creative Drawing Task (Tablet)

Following the paper drawings, participants completed a digital drawing task on a Samsung S9 tablet using a Samsung Pen. Only Cue 2 (Figure 1) was presented on the screen. Drawing parameters were standardized (Turnip Pen, brush size 30.0, black), and the undo function was disabled to mirror the non-erasable paper condition and encourage spontaneous corrections. Although the tablet task allows fine-grained recording of drawing dynamics, it is not analyzed in the present thesis.

- Participants had 3 minutes to complete the drawing.
- Instructions were identical to the paper task, emphasizing creativity.
- Screen recording captured the drawing process for potential future analysis.
- Each participant completed one tablet drawing.

3.4.3. Spiral Tracing Task

Participants also completed a spiral tracing task commonly used to quantify fine motor control in neurological research (Aldhyani et al., 2024). Participants traced a pre-drawn spiral on the tablet, starting at the outer edge and moving inward. Drawing parameters were identical to the tablet drawing task, except the pen color was red (Turnip Pen, brush size 30.0).

Participants traced until they indicated they were finished, with the process recorded for future analysis.

This task provides objective measures of fine motor control, including movement velocity, acceleration, smoothness, path deviation, and completion time (Yoon & Ahn, 2023). While not analyzed here, these data allow for future examination of the relationship between fine motor control and structural drawing properties.

3.5. Image Analysis – Aesthetic Toolbox

To address the methodological limitations identified in the preceding review, particularly the reliance on subjective creativity measures and small-scale stylistic analyses, the present study employed the Aesthetic Toolbox (Redies et al., 2025) to extract quantitative image features from the drawings. As outlined in Section 2.5, prior research on artistic change in PD has often relied on self-report, qualitative description, or isolated computational metrics, limiting reproducibility and multivariate characterization of visual output.

The Aesthetic Toolbox is an open-access computational framework designed to provide standardized, reproducible measures of visual properties associated with aesthetic perception. By quantifying objective image features rather than subjective judgements of creativity or artistic quality, this approach enables systematic comparison of low-level structural properties across groups.

Although termed the Aesthetic Toolbox, the extracted features consist of objective, low-level image statistics (e.g., fractal dimension, Fourier slope, spatial distribution) rather than subjective evaluations of aesthetic quality. The toolbox computes a broad range of image properties, including measures of contrast, complexity, symmetry, balance, Fourier spectrum characteristics, fractal dimension, self-similarity, entropy-based metrics, and convolutional neural network-derived features. All drawings in the present study were monochrome; therefore, analyses were restricted to grayscale-based properties. Although the Aesthetic Toolbox extracted 24 image features in total (see Table 2), the feature Variability was not included in the inferential statistical analyses due to its extremely small numeric scale, which prevented stable estimation in the statistical models. However, it was retained in the machine-learning analyses. As it showed negligible importance in predictive modeling, its exclusion from the inferential analyses did not affect the interpretation of results.

The toolbox integrates original scripts from multiple research groups and has been translated into Python 3, facilitating transparent and consistent feature extraction (Redies et al., 2025). The Aesthetic Toolbox was selected to address known limitations in comparability across studies arising from the use of heterogeneous artistic measures and analysis pipelines.

Table 2

Description of Image Properties

Image Property	Description
RMS contrast	Variance in brightness; higher contrast = greater visual salience.
Lightness entropy	Unpredictability of pixel brightness (L-channel, Lab* space); higher values indicate more varied and evenly distributed light–dark intensities across the image.
Complexity (HOG)	Lightness and color change across the image; higher values indicate dramatic changes in brightness.
Edge density	Image complexity via Gabor filters detecting local brightness changes.
Balance	Distribution of pixel intensities around image's vertical and horizontal axes; higher imbalance reflects a composition with stronger visual weight on one side.
Deviation of the Center of Mass-x-	How balanced an image appears by comparing the location of its "perceptual center of mass" to the geometric center of the frame. Pixel brightness is treated as visual weight (darker = heavier); the distance

Image Property	Description
position (DCM-x-position)	between the perceptual and geometric centers is expressed as percentage of maximum possible deviation; lower values = greater balance; higher values = visual weight shifted away from the center. DCM-x-position is the horizontal deviation. Represents how much the mass of the image is shifted left or right from the center.
DCM-y-position	DCM-y-position is the vertical deviation. Represents how much the mass of the image is shifted up or down the center.
Mirror symmetry	Pixel-based measure of vertical and horizontal symmetry in composition; higher values indicate more regular, mirror-like structure.
Left–right symmetry (CNN)	CNN-detected low-level features (e.g., edges, blobs, simple patterns) on the left vs. right halves of the image. Higher values = stronger perceptual left–right symmetry.
Up–down symmetry (CNN)	Similarity of CNN-extracted features between the upper and lower portions of the image. Higher values = greater vertical (up-down) symmetry.
Combined symmetry (CNN)	Aggregates Left–right and Up–down CNN symmetry scores into a single index capturing overall perceptual symmetry based on early-vision feature detection.
Fourier spectrum slope	Balance between fine details (small features) and broad features (large patterns in an image); natural images ≈ 1.2.

Image Property	Description
Fourier spectrum sigma	Deviation from a straight-line log-log Fourier spectrum; lower = more natural.
2D fractal dimension	Self-similarity and edge complexity across scales in 2D space; higher values indicate more intricate, repeating patterns.
3D fractal dimension	Self-similarity and complexity in 3D space (including brightness/lightness); higher values indicate more intricate, detailed, and visually rich patterns.
Self-similarity (PHOG-based)	How similar smaller parts of an image are to the whole, based on shape and structure. Uses a Pyramid Histogram of Oriented Gradients (PHOG) to compute gradient orientations at multiple spatial scales; higher values = greater self-similarity and structural coherence. Visually pleasing images, like traditional paintings, tend to have higher scores.
Self-similarity (CNN-based)	How similar smaller parts of an image are to the whole using a Convolutional Neural Network (CNN). Analyzes basic visual features (edges, colors, patterns) at multiple spatial scales and compares feature distributions across image sections. Higher scores (closer to 1) = greater self-similarity, reflecting structural coherence and perceptual similarity as humans might perceive it.

Image Property	Description
Homogeneity	Distribution of black-and-white (or high-contrast) feature; spatial arrangement of pixels are relevant; high values = well-organized, balanced distribution of features, often perceived as orderly or harmonious; low values = clustering of dark/light pixels, uneven, visually fragmented appearance.
Anisotropy (HOG)	Directional dominance of edges and patterns in an image. Low values = edges are evenly distributed across all orientations, contributing to a sense of visual balance. High values = certain directions (e.g., horizontal or vertical) dominate, creating a more structured or rigid appearance.
1st-order edge-orientation entropy (EOE)	Distribution of edge orientations across the image, ignoring spatial location. High values = edges are evenly spread in all directions (e.g., curved or varied shapes); low values = uneven or dominant orientations (e.g., sharp, angular shapes).
2nd-order edge-orientation entropy (EOE)	Independence of edge orientations relative to other edges in the image. High values = edge directions are unpredictable from one part of the image to another; low values = more predictable, patterned arrangements (e.g., grids or aligned structures).
Sparseness	How focused the CNN responses are on specific areas of the image. High values = that only a few regions strongly activate the network (dominant features); low values = more evenly distributed activation

Image Property	Description
	across the image (rich detail). Traditional artworks tend to show low sparseness due to complex, varied content.
Variability	How much CNN responses differ across the image. High values = the network responds very differently across regions, reflecting diverse patterns, textures, or elements. Low values = consistent responses, suggesting repetitive or uniform structures, related to self-similarity.

3.6. Statistical Analyses

All statistical analyses were conducted using JASP (JASP Team, 2025) and R Studio. Preliminary data inspection, basic descriptive statistics, and data organization were supported using Microsoft Excel.

JASP was used for inferential statistical analyses, including independent samples *t*-tests, univariate analyses of variance (ANOVAs), multivariate analyses of variance (MANOVAs), and mixed (repeated-measures) ANOVAs. Effect sizes for ANOVA-based analyses are reported as eta squared (η^2) and were interpreted using conventional benchmarks, with values of approximately .01, .06, and .14 indicating small, medium, and large effects, respectively (Cohen, 1988).

Principal component analysis (PCA) was conducted in R to reduce the dimensionality of the computational image feature set and to identify latent components capturing shared variance among structural image properties. All statistical analyses were exploratory in nature and aimed to identify potential group-related patterns in drawings and to inform future confirmatory research**.**

3.7. Machine Learning Approach

To complement inferential statistical analyses with a predictive framework, a supervised machine-learning approach was applied to examine whether computational image features extracted from the drawings could be used to classify participants into diagnostic groups at the individual-sample level.

3.7.1. Gradient-Boosted Tree Classification (LightGBM)

Classification was performed using a gradient-boosted decision tree model implemented with LightGBM (Light Gradient Boosting Machine). Gradient-boosted tree models were selected due to their strong performance on tabular data, robustness to multicollinearity and non-normal feature distributions, and their ability to model nonlinear interactions between predictors. In addition, tree-based models are well suited for datasets with a moderate number of observations and a relatively high-dimensional feature space.

The input features consisted of the computational image features extracted from each drawing, corresponding to those used in the MANOVA and mixed ANOVA analyses. The target variable was group membership, comprising three classes: individuals with Parkinson's disease (PD), age-matched healthy controls (HC), and a younger student control group (SC).

All machine-learning analyses were implemented in Python using established libraries. Model development, hyperparameter tuning, and evaluation procedures were conducted using a standardized and transparent analysis pipeline developed in collaboration with an experienced researcher.

3.7.2. Cross-Validation and Model Evaluation

To prevent data leakage and inflated performance estimates, model evaluation was conducted using a repeated group-aware k-fold cross-validation procedure. Group labels were defined at the participant level, ensuring that drawings from the same individual were never split across training and test folds. This approach is particularly important when multiple drawings per participant are included, as it prevents overly optimistic performance estimates arising from within-subject similarity.

Cross-validation was repeated multiple times with different random fold assignments to obtain stable estimates of classification performance. Model performance was quantified

using balanced classification accuracy, which accounts for potential class imbalance. Mean, standard deviation, and median accuracy values were computed across repetitions.

3.7.3. Control Analysis: Label Shuffling

To assess whether classification performance exceeded chance level, a label-shuffling control analysis was performed. Group labels were randomly permuted while keeping the feature data unchanged, and the full classification and cross-validation procedure was repeated using the same group-aware splits. Classification accuracy obtained from the original labels was then compared to the distribution of accuracies obtained under label shuffling. Statistical significance was assessed by comparing original-label performance against the shuffled-label distribution.

3.7.4. Model Interpretation: SHAP Analysis

To enhance model interpretability, feature importance was assessed using SHAP (SHapley Additive exPlanations) values, computed using TreeSHAP, which provides exact and additive feature attributions for tree-based models. SHAP values quantify the contribution of each feature to a model's predictions, expressed as changes in log-odds relative to the expected model output.

Mean absolute SHAP values were used to rank features according to their overall importance for group classification. In addition to a global importance analysis, class-specific SHAP values were computed separately for each diagnostic group to examine whether distinct feature patterns characterized classification decisions for PD, HC, and SC participants. Statistical significance of SHAP values was assessed using permutation-based testing procedures.

4. Results

4.1. Participant Characteristics

A total of 131 participants were included in the primary analyses, comprising 62 individuals diagnosed with Parkinson's disease (PD) and 69 healthy control participants (HC). An independent samples *t*-test ensured the PD group and the HC were age-matched. The analysis revealed no significant age difference between groups, $t(130) = -0.129$, $p = .898$. Mean age was 65.56 years (SD = 9.40) in the PD group and 65.13 years (SD = 10.29) in the HC group. The PD group consisted of 41 females and 21 males, while the HC group included 44 females and 25 males. No significant differences in age or gender distribution were observed between groups.

For exploratory machine-learning analyses, an additional younger student control (SC) group was included. This group consisted of 48 female participants with a mean age of 21.3 years (SD = 3.9; range = 18–36 years). The student control group was not included in inferential statistical analyses comparing PD and HC participants.

An overview of key sociodemographic characteristics of the PD and HC groups is provided in Table 3.

Table 3

Sociodemographic characteristics

Characteristic	**HC (*n* = 69)**	**PD (*n* = 62)**
Age, *M* (SD)	65.13 (10.38)	65.56 (9.46)
Female, *n* (%)	44 (63.8%)	41 (66.1%)
Male, *n* (%)	25 (36.2%)	21 (33.9%)

Note. M = mean; SD = standard deviation.

4.2. Feature-Level Analyses

Descriptive statistics for all extracted image features are presented in Table 4. Across drawings, substantial variability was observed in measures of multiscale structure, spatial distribution, and contrast-related properties. To illustrate how variation in computational features manifests visually, Figure 2 presents representative drawings with relatively high and low values for selected features (e.g., fractal dimension, symmetry, and contrast). For completeness, Appendix 2 presents representative drawings corresponding to the lowest and highest values of each computational feature across groups. These examples demonstrate how the extracted image statistics correspond to observable differences in structural complexity and compositional organization.

Table 4

Descriptive Statistics of Computational Features

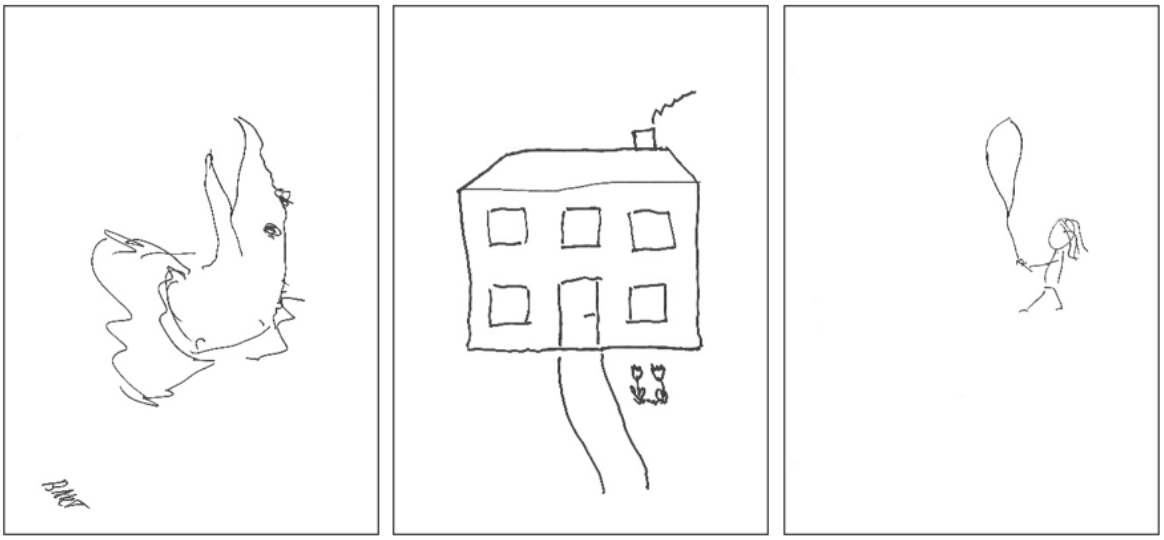
Features	**HC *M*(SD)**	**PD *M*(SD)**	**Minimum**	**Maximum**
RMS contrast	13.94 (3.41)	12.22 (3.10)	6.18	23.27
Lightness entropy	0.83 (0.40)	0.73 (0.29)	0.20	2.65
Complexity	1.92 (1.07)	1.75 (0.73)	0.32	6.42
Edge density	74.01 (34.61)	60.19 (27.49)	14.23	180.06
Mirror symmetry	0.56 (0.54)	0.37 (0.31)	0.04	3.51
Balance	32.82 (12.70)	35.00 (13.10)	12.41	69.38
DCM distance	21.92 (9.32)	21.63 (8.37)	6.64	45.20
DCM-x-position	-0.02 (0.04)	-0.00 (0.05)	-0.12	0.14
DCM-y-position	0.08 (0.20)	-0.01 (0.16)	-0.65	0.58

CNN symmetry left-right	0.40 (0.06)	0.38 (0.60)	0.26	0.54
CNN symmetry up-down	0.33 (0.06)	0.33 (0.05)	0.17	0.50
CNN symmetry combined	0.29 (0.06)	0.29 (0.05)	0.15	0.47
Fourier slope	-1.82 (0.16)	-1.65 (0.20)	-2.31	-1.34
Fourier sigma	0.09 (0.04)	0.06 (0.04)	0.01	0.22
2D fractal dimension	1.32 (0.05)	1.34 (0.05)	1.19	1.23
3D fractal dimension	2.40 (0.07)	2.37 (0.07)	2.23	2.64
Self-similarity (PHOG)	0.38 (0.15)	0.37 (0.14)	0.05	0.68
Self-similarity (CNN)	0.51 (0.26)	0.51 (0.24)	0.09	0.84
Homogeneity	83.62 (10.28)	83.15 (10.10)	49.26	97.90
Anisotropy	0.00100 (0.00025)	0.00096 (0.00020)	0.00051	0.00200
1st order EOE	4.24 (0.22)	4.30 (0.12)	3.60	4.51
2nd order EOE	4.30 (0.21)	4.34 (0.17)	3.58	4.54
Sparseness	0.00100 (0.00027)	0.00100 (0.00023)	0.00040	0.002

Note. Values represent mean (*M*) and standard deviation (SD) of each computational image feature. All features were extracted using the Aesthetic Toolbox (Redies et al., 2025). Small values are reported to five decimal places for readability.

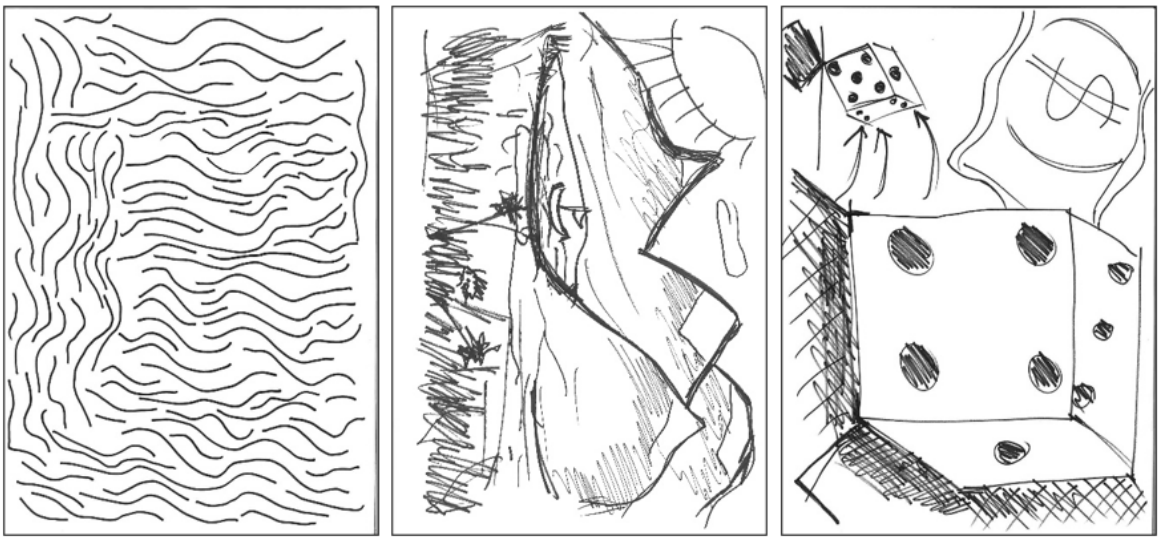
Figure 2

Low in RMS contrast



PD (3.32) HC (3.77) PD (4.59)

High in RMS contrast

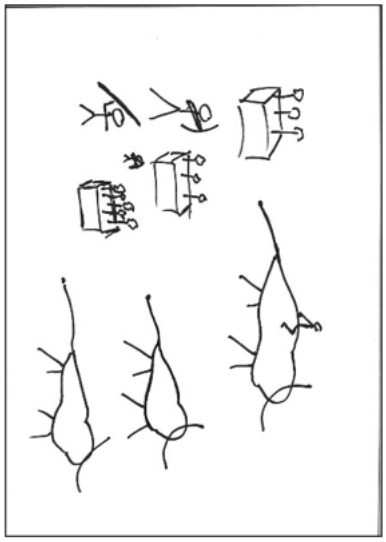


SC (25.20) HC (25.06) SC (24.68)

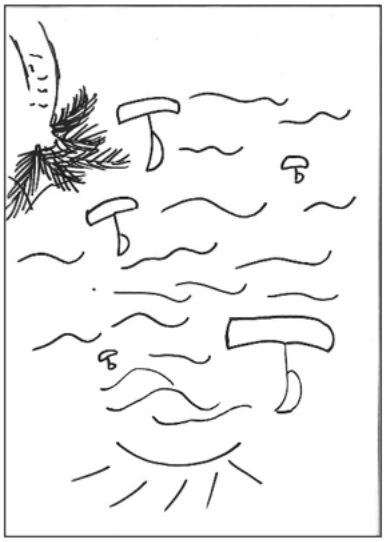
Example Drawings Illustrating Lowest and Highest Values Across Selected Computational Image Features

Low in 3D fractal dimension

SC (1.25)



SC (1.25)



SC (1.26)

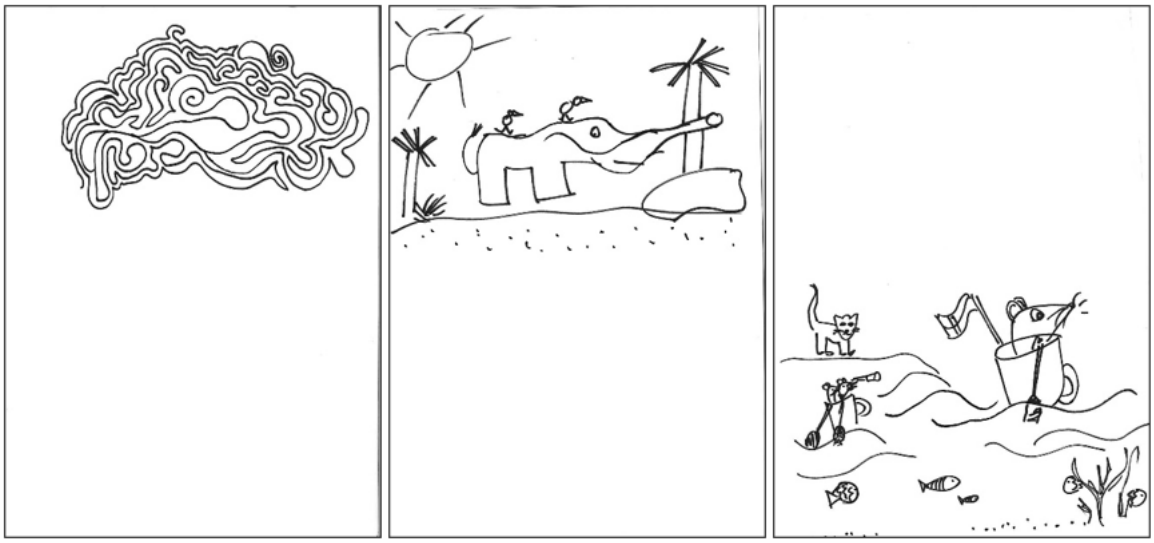
High in 3D fractal dimension

HC (2.82)

PD (2.67)

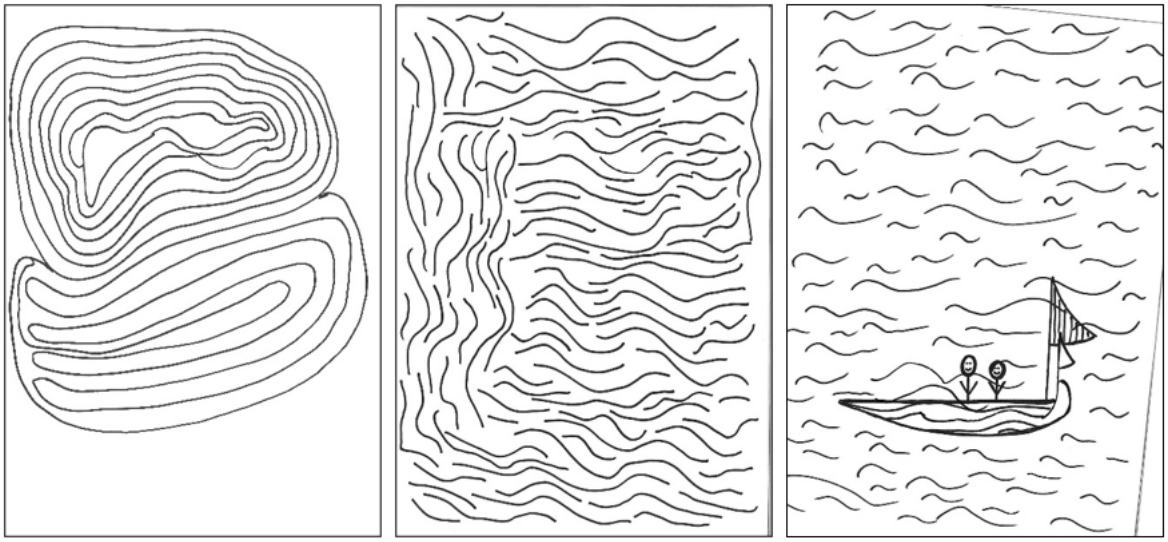
PD (2.64)

Low in CNN symmetry left-right & up-down



SC (0.08) SC (0.08) SC (0.08)

High in CNN symmetry left-right & up-down:



HC (0.67) SC (0.56) SC (0.55)

Note. Each feature is illustrated by three drawings with the lowest and three with the highest values. Labels beneath each drawing indicate group membership (PD = Parkinson's disease; HC = healthy control; SC = student control) and the corresponding feature value. The examples illustrate the visual range captured by the computational feature and provide qualitative context for the quantitative analyses.

4.1.1. Multivariate Analysis of Variance (MANOVA)

A one-way multivariate analysis of variance (MANOVA) was conducted to examine whether PD and HC participants differed across a set of computational image features. MANOVA was selected to account for correlations among features and to control for inflation of Type I error associated with multiple univariate tests. Because of the high dimensionality and multicollinearity of the extracted features, a single MANOVA including all cue-specific variables was not feasible. Therefore, feature values were averaged across cues for each participant prior to multivariate analysis.

The multivariate test using Pillai's Trace revealed a significant overall effect of Group, $V = .410$, $F(23, 107) = 3.23$, $p < .001$, indicating that the combined set of computational image features reliably differentiated PD drawings from those of HC participants. Although the assumption of multivariate normality was violated (Shapiro–Wilk test, $p < .001$), Pillai's Trace is considered robust to such deviations and was therefore used for interpretation. Box's *M* test indicated a violation of the homogeneity of covariance matrices ($p < .001$); however, given the robustness of Pillai's Trace to this violation, the multivariate results were interpreted with appropriate caution.

4.1.2. Follow-up Univariate Analyses

Given the significant multivariate group effect, follow-up univariate analyses of variance were conducted to identify which individual computational image features contributed to the overall group difference. Significant group differences were observed for eight features (see Table 5).

Compared to PD participants, HC participants exhibited higher RMS contrast, Edge density, Mirror symmetry, DCM-y-position, Fourier sigma, and 3D fractal dimension. In contrast, PD drawings showed higher 2D fractal dimension values and less negative Fourier slope values relative to HC drawings. Effect sizes ranged from small to large, indicating variability in the magnitude of group differences across features. Specifically, two features showed large group effects ($\eta^2 = .182$ and .153), two features demonstrated medium-sized effects ($\eta^2 = .066$ and .062), and the remaining features exhibited small to small-to-medium effects (η^2 range = .031–.047). All other features did not show significant group differences ($p > .05$).

Table 5

Follow-Up Univariate ANVOVAs for Computational Image Features

Features	***F*(1,129)**	***p***	**η^2**	**Direction**
RMS contrast	9.104	.003	.066	HC > PD
Edge densitiy	6.307	.013	.047	HC > PD
Mirror symmetry	6.003	.016	.044	HC > PD
DCM-y-position	8.593	.004	.062	HC > PD
Fourier Slope	28.675	< .001	.182	HC < PD*
Fourier Sigma	23.295	< .001	.153	HC > PD
2D fractal dimension	4.151	.044	.031	HC < PD
3D fractal dimension	5.561	.020	.041	HC > PD

Note. *Fourier slope values were less negative in PD drawings. Group means and standard deviations are reported in Appendix 3.

4.3. Repeated-Measures Analyses (Mixed ANOVA)

To examine within-subject effects of drawing cue and between-subject effects of group and gender, repeated-measures analyses of variance (mixed ANOVAs) were conducted separately for each computational image feature. Cue (three levels) was specified as a within-subject factor, while group (PD vs. HC) and gender were included as between-subject factors. Participants were age-matched across groups; therefore, age was not included as a covariate. When the assumption of sphericity was violated, Greenhouse–Geisser corrections were applied.

Between-subjects group effects observed in the mixed ANOVAs largely mirrored the results of the MANOVA conducted on cue-averaged features, indicating that group differences were stable across cue conditions.

4.3.1. Between-Subjects Effects of Group

Consistent with the MANOVA results, significant between-subjects effects of group were observed for several computational image features, indicating robust differences between PD and HC participants averaged across cue conditions. Specifically, significant group effects were found for RMS contrast, Edge density, Mirror symmetry, DCM-y-position, Fourier slope, Fourier sigma, 3D fractal dimension, and 1st-order EOE.

For features in which Levene's test indicated violations of the homogeneity of variance assumption, Welch's ANOVA was applied. Detailed test statistics and effect sizes are reported in Table 6.

Table 6

Between-Subjects Effects of Group on Computational Image Features

Feature	***F*(df$_1$, df$_2$)**	***p***	**η^2**	**Direction**
RMS contrast	*F*(1, 125) = 7.414	.007	.046	HC > PD
Edge density	*F*(1, 125) = 4.885	.029	.030	HC > PD
Mirror symmetry	*F*(1, 125) = 4.481	.036	.027	HC > PD
DCM-y-position	*F*(1, 126) = 12.63	.003	.027	HC > PD
Fourier slope	*F*(1, 125) = 25.936	< .001	.131	HC < PD
Fourier sigma	*F*(1, 125) = 20.554	< .001	.107	HC > PD
3D fractal dimension	*F*(1, 125) = 5.326	.023	.027	HC > PD
1st-order EOE[1]	*F*(1, 108.82) = 4.04	.047	.029	HC < PD

Note. Welch's ANOVA was applied where Levene's test indicated unequal variances.

4.3.2. Within-Subjects Effects of Cue

To assess whether the type of pre-drawn line influenced structural characteristics independently of diagnosis, within-subject main effects of cue were examined. Significant main effects of cue were observed for multiple features (see Table 7), demonstrating that drawing cues systematically modulated several image properties across participants.

Cue-related effects were found for Mirror symmetry, DCM distance, CNN-based symmetry measures (left–right, up–down, and combined), Fourier slope, Fourier sigma, 3D fractal dimension, Anisotropy, and both 1st and 2nd -order EOE. Effect sizes ranged from small to large (η^2 = .009–.169), indicating varying sensitivity of features to cue manipulations. No significant cue effects were observed for the remaining features.

Where applicable, Bonferroni-corrected post hoc pairwise comparisons were conducted to further characterize significant cue-related effects; detailed post hoc results are reported in Appendix 4.

Table 7

Within-Subjects Main Effects of Cue on Computational Image Features

Feature	***F*(df_1, df_2)**	***p***	**η^2**
Mirror symmetry	*F*(2, 250) = 7.209	< .001	.011
DCM distance	*F*(2, 250) = 4.160	.017	.018
CNN symmetry left-right[1]	*F*(1.90, 237.397) = 27.911	<.001	.111
CNN up-down	*F*(2, 250) = 11.259	<.001	.047
CNN combined	*F*(2, 250) = 8.489	<.001	.036
Fourier slope	*F*(2, 250) = 5.186	.006	.009
Fourier sigma	*F*(2, 250) = 11.935	< .001	.097

3D fractal dimension	$F(2, 250) = 6.442$	.002	.016
Anisotropy[1]	$F(1.795, 224.424) = 9.636$	< .001	.022
1st -order EOE [1]	$F(1.421, 177.563) = 46.111$	<.001	.169
2nd -order EOE[1]	$F(1.548, 193.542) = 18.039$	<.001	.059

Note. Greenhouse–Geisser corrections were applied when the assumption of sphericity was violated.

4.3.3. Interaction Effects Involving Cue

Interaction effects involving cue were limited. A significant cue × group interaction was observed for Fourier sigma, indicating differential cue-related modulation between PD and HC participants. In addition, first-order EOE exhibited both cue × group and cue × gender interactions, while 2nd-order EOE showed a cue × gender interaction. Significant interaction effects involving cue are summarized in Table 8.

No other interaction effects reached statistical significance, suggesting that cue-related changes in most features were largely comparable across diagnostic groups and genders.

Table 8

Significant Interaction Effects Involving Cue

Feature	Interaction	$F(df_1, df_2)$	p	η^2
Fourier sigma	Cue × Group	$F(2, 250) = 4.18$	.016	.007
1st-order EOE	Cue × Group	$F(2, 250) = 4.87$	.017	.018
1st-order EOE	Cue × Gender	$F(2, 250) = 3.92$	.035	.014
2nd-order EOE	Cue × Gender	$F(2, 250) = 3.53$	.042	.011

Note. Greenhouse–Geisser corrections were applied where the assumption of sphericity was violated.

4.3.4. Gender Effects

Main effects of gender were generally small and infrequent. A significant main effect of gender was observed for DCM-x-position, with female participants showing higher values than male participants. No other features demonstrated significant gender-related differences.

4.4. Principal Component Analysis (PCA)

4.4.1. Assumption Checks (KMO & Bartlett)

Prior to conducting the principal component analysis (PCA), the suitability of the data for dimensionality reduction was evaluated using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. The overall KMO measure was .83, indicating good sampling adequacy. Individual MSAs ranged from .41 to .94, with the majority exceeding .60., suggesting that the computational image features shared sufficient common variance to justify PCA. Inspection of individual measures of sampling adequacy (MSA) showed

that most variables exceeded the commonly recommended threshold of .60, indicating acceptable contributions to the common factor structure. A small number of variables exhibited lower MSA values, reflecting weaker shared variance, but were retained given the exploratory nature of the analysis.

Bartlett's test of sphericity was statistically significant, indicating that the correlation matrix significantly differed from an identity matrix and confirming that the intercorrelations among variables were sufficient for PCA.

Together, these diagnostics supported the appropriateness of applying PCA to the extracted computational image feature set.

4.4.2. Principal Component Extraction

PCA was conducted on standardized computational image features averaged across cue conditions. Features with zero variance across observations (e.g., image size and aspect ratio) were excluded prior to component extraction. Components were extracted using eigenvalue decomposition of the correlation matrix. Based on inspection of the scree plot and the cumulative proportion of explained variance, the first four principal components (PC1–PC4) were retained for interpretation.

These four components accounted for 71.5% of the total variance, with PC1 explaining 40.1%, PC2 explaining 12.9%, PC3 explaining 11.1%, and PC4 explaining 7.4% of the variance. Component loadings with absolute values ≥ .40 were considered substantial and are summarized in Table 9.

4.4.3. Component Structure and Interpretation

Examination of the unrotated component loadings revealed a coherent and interpretable structure:

- PC1 (Visual Complexity and Texture) was characterized by high positive loadings on RMS contrast, Lightness entropy, Complexity, Edge density, Self-similarity (PHOG and CNN), and Homogeneity, along with negative loadings on Sparseness, Balance, and Anisotropy. This component reflects overall visual richness and structural density, contrasting complex, highly textured drawings with sparse and visually simple ones.

- PC2 (Global Symmetry and Fractal Structure) was defined primarily by Mirror symmetry and 3D fractal dimension, with additional contributions from RMS contrast and entropy-related measures. This component captures global structural organization and symmetry-related properties of the drawings.
- PC3 (Edge Orientation versus CNN-Based Symmetry) showed strong positive loadings on 1st and 2nd -order edge orientation entropy and negative loadings on CNN-derived symmetry measures. This component reflects a contrast between local edge orientation complexity and machine-derived symmetry estimates.
- PC4 (Spectral and Spatial Composition) was dominated by Fourier-based features (positive loadings on Fourier slope and negative loadings on Fourier sigma), 2D fractal dimension, and spatial distribution metrics, including DCM-y-position. This component represents frequency-domain structure and spatial composition of the drawings.

Several variables exhibited moderate cross-loadings (e.g., RMS contrast and lightness entropy), indicating shared variance across multiple components. Overall, the component structure was stable and broadly consistent with the underlying organization of the computational image feature set.

Table 9

Principal Component Loadings for PC1–PC4

Variable	PC1	PC2	PC3	PC4
Mirror symmetry		.39		
CNN symmetry (left–right)			−.35	
CNN symmetry (up–down)			−.32	
CNN symmetry (combined)			**−.41**	
Fourier slope		−.23		**.45**

Variable	PC1	PC2	PC3	PC4
Fourier sigma			−.22	**−.51**
2D fractal dimension		.23	.27	**.45**
3D fractal dimension		**.46**		
1st-order EOE			.39	
2nd-order EOE			.38	
DCM-y-position				−.26
Edge density	.29			
Complexity	.28			
Lightness entropy	.28			
RMS contrast	.27			
Self-similarity (PHOG)	.29			
Self-similarity (CNN)	.28			
Homogeneity	.29			
Sparseness	−.31			
Balance	−.27			
Anisotropy	−.27			

Note. Loadings ≥ |.40| are bold.

4.4.4. Multivariate Analysis of Principal Component Scores

To examine group differences between HC and PD participants across the low-dimensional feature structure identified by the PCA, a one-way MANOVA was conducted on the first four principal component scores (PC1–PC4). These components collectively explained 71.5% of the total variance in the computational image feature set.

The multivariate effect of group was statistically significant, as indicated by Pillai's Trace, V = .218, F(4, 386) = 26.92, p < .001. This result indicates that HC and PD participants differed significantly on the combined set of principal components.

4.4.5. Univariate Follow-up Analyses

Follow-up univariate analyses were conducted to identify which principal components contributed to the significant multivariate group effect. Significant group differences were observed for PC2 and PC4, whereas no significant differences were found for PC1 or PC3 (see Table 10). Specifically, PC2 (global symmetry and fractal structure) differed significantly between groups, $F(1, 389) = 29.84$, $p < .001$. Healthy control participants exhibited higher PC2 scores ($M = 0.44$, SD = 1.81) compared to PD participants ($M = -0.50$, SD = 1.55), indicating greater symmetry-related and fractal organization in HC drawings.

In addition, PC4 (spectral and spatial composition) showed a robust group difference, $F(1, 389) = 61.49$, $p < .001$. PD participants scored higher on PC4 (M = 0.52, SD = 1.31) than healthy controls ($M = -0.46$, SD = 1.18), reflecting greater alterations in frequency-domain and spatial composition features. These group differences are illustrated in Figure 2, which displays group means and 95% confidence intervals for PC2 and PC4.

No significant group effects were observed for PC1 (overall visual complexity), $F(1, 389) = 1.43$, $p = .233$, or PC3 (edge orientation versus CNN-based symmetry), $F(1, 389) = 2.62$, $p = .106$.

Together, these findings indicate that group differences between PD and HC participants were primarily driven by alterations in symmetry-related and frequency-based dimensions, rather than by general visual complexity or locally derived symmetry features.

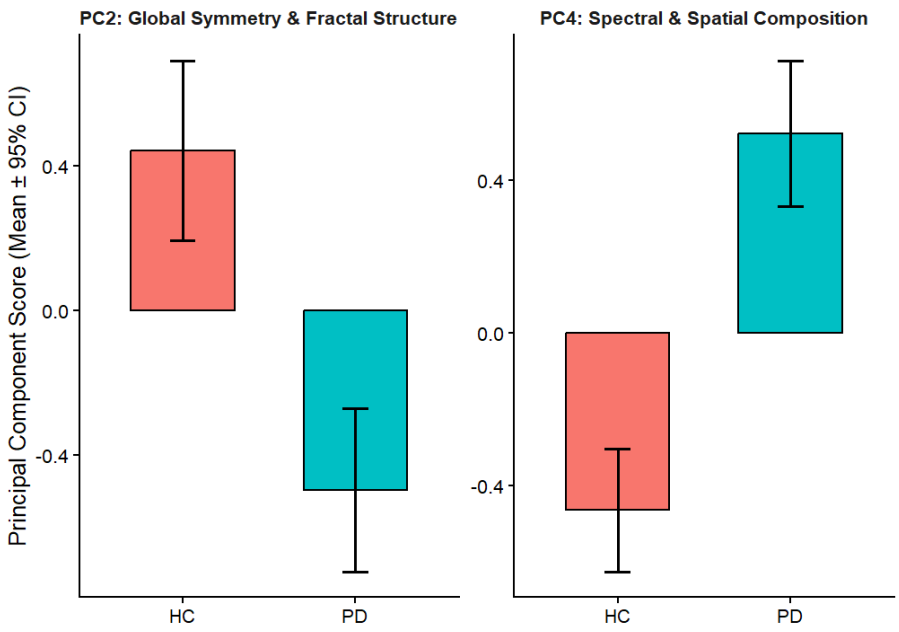
Table 10

Group Means (SD) for Principal Component Scores

Component	HC Mean (SD)	PD Mean (SD)
PC1	0.18 (3.29)	−0.20 (2.88)
PC2	0.44 (1.81)	−0.50 (1.55)
PC3	−0.13 (1.79)	0.14 (1.43)
PC4	−0.46 (1.18)	0.52 (1.31)

Figure 2

Group Means and 95% Confidence Intervals for PC2 and PC4.



Note. Group differences in principal component scores for PC2 and PC4. Bars represent group means and error bars indicate 95% confidence intervals. PC2 reflects global symmetry and fractal structure, with healthy controls showing higher scores than Parkinson's disease participants. PC4 reflects spectral and spatial composition, with Parkinson's disease participants showing higher scores than healthy controls.

4.5. Machine-Learning Classification and Feature Importance

4.5.1. Multiclass Classification of Drawing Groups Using Gradient-Boosted Trees

While the PCA and subsequent multivariate statistical tests demonstrated robust group differences in the overall structural image features, these analyses were inferential in nature and focused on explaining variance at the group level. To complement these findings with a predictive approach, we conducted a supervised machine-learning analysis using a gradient-boosted decision tree classifier (LightGBM). In contrast to PCA and MANOVA, which test whether groups differ on average, this approach assesses whether multivariate feature patterns are sufficiently distinctive to enable reliable classification of individual drawings. The machine-learning analysis therefore provides an important extension of the statistical results by evaluating the discriminative power of the extracted computational image features at the individual-sample level.

The LightGBM classifier was trained and evaluated using repeated group-aware cross-validation to prevent information leakage across participants. Across repetitions, the classifier achieved a mean balanced classification accuracy of 0.794 (SD = 0.041; median = 0.799) when trained on the original data. In contrast, performance on shuffled-label control data was substantially lower (M = 0.340, SD = 0.060; median = 0.341), corresponding closely to chance-level performance for a three-class problem. The difference between original and shuffled data performance was statistically significant ($p \leq .001$), indicating that the classifier learned meaningful structural image features rather than chance associations (Figure 3).

It should be noted that DCM-x-position and DCM-y-position values were not available for the SC group due to incomplete feature extraction in the original dataset. These missing entries were retained as empty values and were not imputed. Consequently, feature importance patterns involving DCM metrics, particularly in relation to the SC group, should be interpreted with appropriate caution.

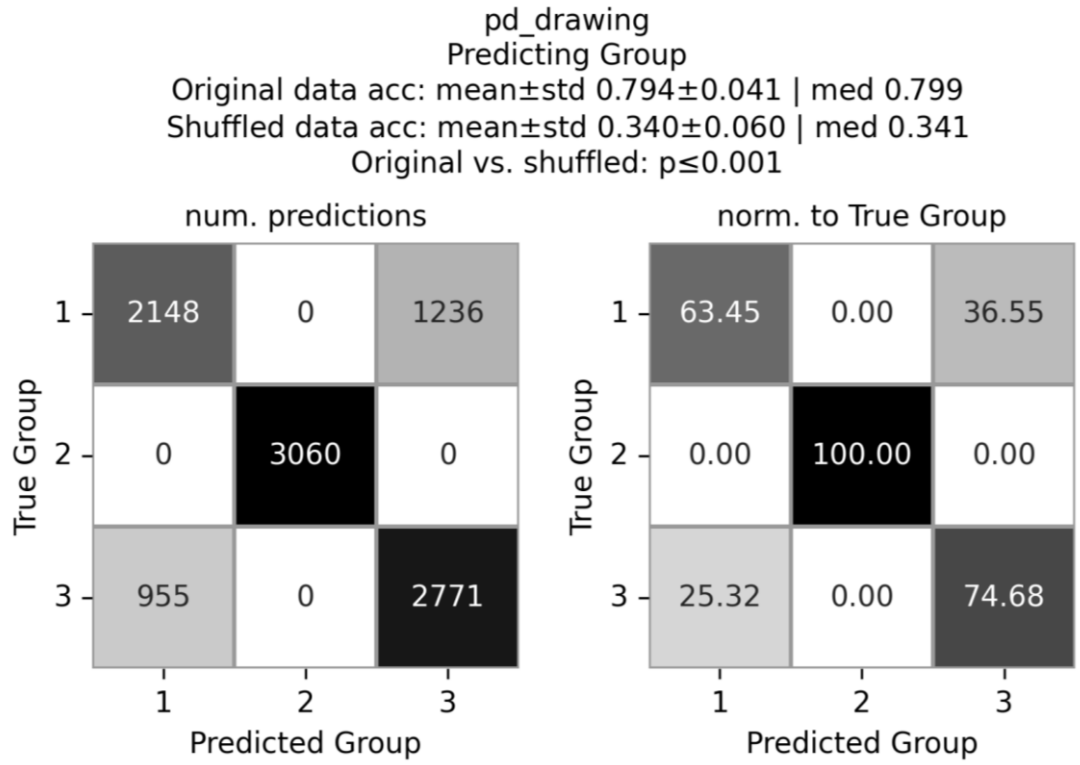
4.5.2. Confusion Matrix and Group-Specific Classification Performance

Inspection of the confusion matrix (Figure 3) revealed distinct patterns of classification performance across groups. Drawings produced by psychology students (Group 2) were classified with near-perfect accuracy (100%), indicating that drawings from younger participants were highly distinguishable from those of older adults.

In contrast, misclassifications occurred primarily between the PD (Group 3) and HC (Group 1) groups. Specifically, PD drawings were most frequently misclassified as HC drawings, and vice versa, reflecting substantial overlap in drawing characteristics within the older adult sample. Despite this overlap, classification accuracy between PD and HC participants remained clearly above chance, suggesting that disease-related differences in drawing features were present but more subtle than age-related effects. These findings indicate that age was the dominant source of separability in the data, while disease-specific effects contributed additional but weaker discriminative information.

Figure 3

Confusion Matrices



Note. Confusion matrices illustrate the classification performance of the machine-learning classifier. The left panel shows absolute prediction counts, whereas the right panel presents row-normalized percentages relative to the true class. Group 1 corresponds to HC, Group 2 to SC, and Group 3 to individuals with PD. Overall classification accuracy for the model trained on the original labels and for the shuffled-label control is reported above each matrix.

4.5.3. Feature Importance Analysis Using SHAP Values

To examine which computational image features contributed most strongly to classification decisions, SHAP (SHapley Additive exPlanations) analyses were conducted using TreeSHAP, which provides exact and additive feature attributions for tree-based models. In addition to an overall importance analysis, class-specific SHAP values were computed separately for each diagnostic group: Parkinson's disease (class 0), psychology students (class 1), and age-matched healthy controls (class 2). This class-wise approach allowed assessment of whether distinct feature patterns characterized the classification of each group.

Across all classes, features with the highest mean absolute SHAP values were predominantly global structural and spatial measures, particularly fractal dimensions and DCM position metrics. In contrast, local texture measures, CNN-derived symmetry indices, and entropy-based features consistently showed low contributions to classification decisions.

Parkinson's Disease Group (Class 0). For drawings classified as PD, the most influential features included DCM-y-position, Fourier slope, Fourier sigma, and complexity-related measures (Figure 4). These results indicate that frequency-domain characteristics and global spatial distribution played a central role in distinguishing PD drawings from those of other groups. Fractal dimensions and RMS contrast also contributed to classification, albeit to a lesser extent. Overall, PD classification relied primarily on features capturing large-scale structure and spatial organization rather than fine-grained local texture.

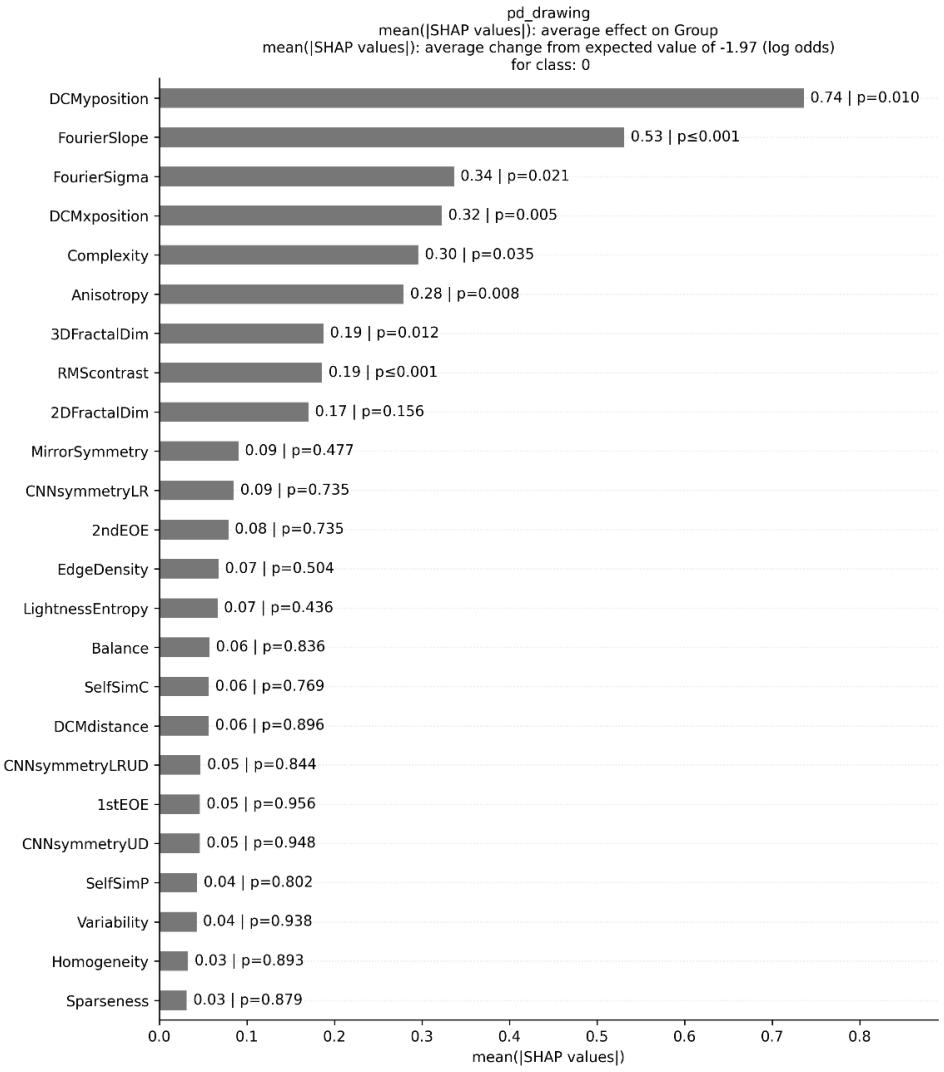
Psychology Student Group (Class 1). Classification of psychology students was driven most strongly by two- and three-dimensional fractal dimensions, as well as DCM-x-position and DCM-y-position (Figure 5). These features reflect multiscale structure and global compositional layout, suggesting that drawings produced by younger participants were characterized by distinctive large-scale organizational properties. Most other features contributed minimally to classification for this group, consistent with the high separability observed in the confusion matrix.

Age-Matched Healthy Control Group (Class 2). For HC, DCM-y-position emerged as the strongest contributor to classification, followed by fractal dimensions and Fourier-based measures (Fourier sigma and slope; Figure 6). RMS contrast showed a modest contribution, whereas CNN-derived symmetry measures, entropy-based features, and balance-related measures again played only a minor role. This pattern closely resembled that observed for the

PD group, consistent with the substantial overlap in classification performance between these two groups.

Figure 4

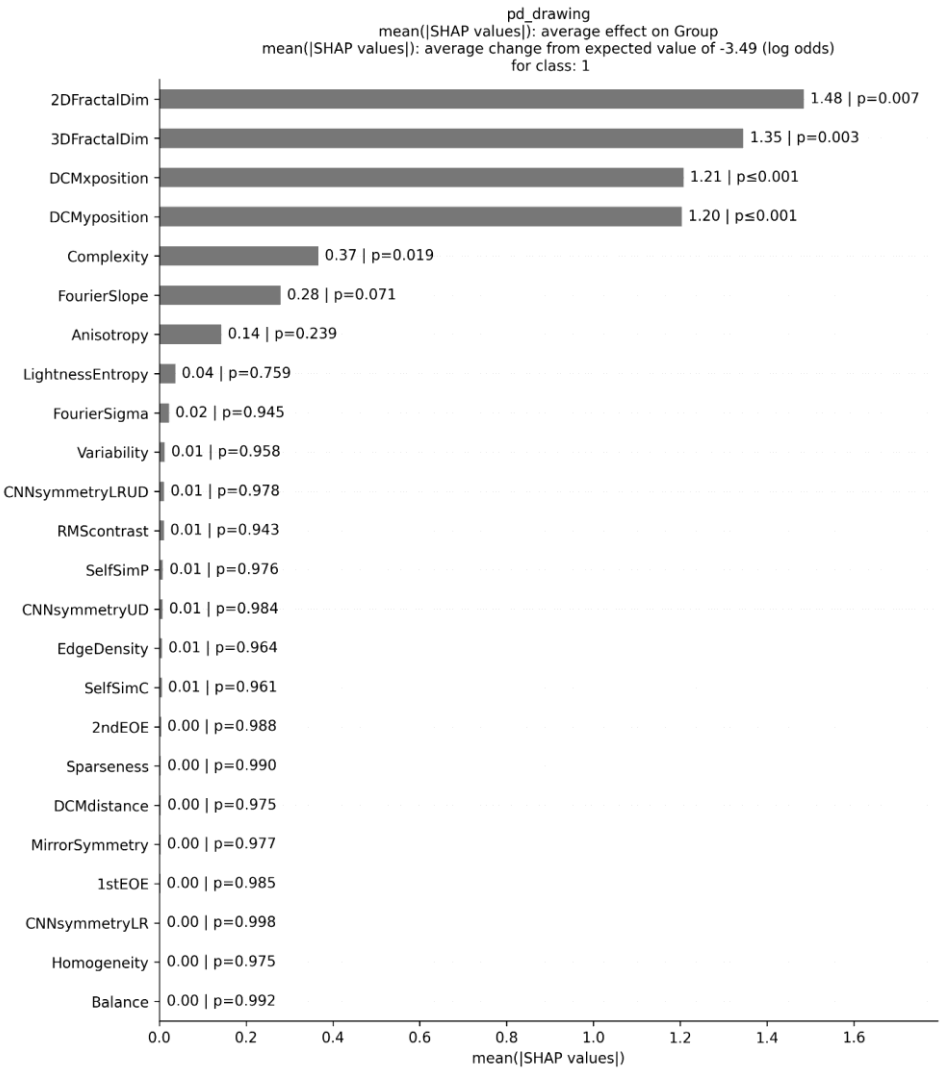
SHAP Values of PD Group



Note. Mean absolute SHAP values reflect the average contribution of each feature to the model's predictions, expressed in log-odds units, and should be interpreted as relative importance rather than effect size.

Figure 5

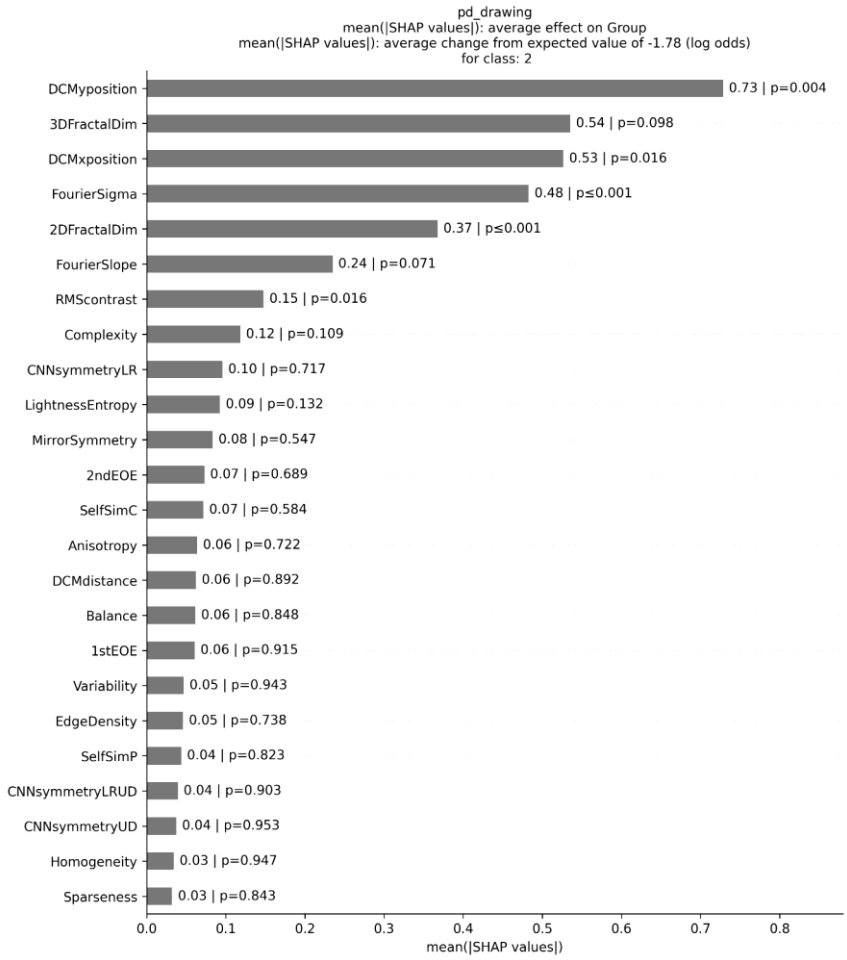
SHAP Values of SC



Note. Mean absolute SHAP values reflect the average contribution of each feature to the model's predictions, expressed in log-odds units, and should be interpreted as relative importance rather than effect size.

Figure 6

SHAP values of HC



Note. Mean absolute SHAP values reflect the average contribution of each feature to the model's predictions, expressed in log-odds units, and should be interpreted as relative importance rather than effect size.

4.5.4. Convergence with Inferential Analyses

Taken together, the SHAP analyses indicate that classification across all groups relied primarily on global spatial layout, scaling properties, and frequency-based structure, rather than fine-grained local texture or algorithmically derived symmetry measures. These patterns closely mirror the results of the PCA and inferential statistical analyses, which also highlighted

the relevance of fractal structure, Fourier-based features, and spatial organization. This convergence across inferential and predictive approaches suggests that the machine-learning model captured meaningful and interpretable aspects of drawing structure rather than spurious feature associations.

5. Discussion

5.1. Aims and Main Findings

The present study examined whether PD is associated with systematic, quantifiable alterations in drawing structure, using computational image analysis to compare individuals with PD to age-matched HC. To address this question, a computational approach was employed, extracting 24 image-based features using the Aesthetic Toolbox (Redies et al., 2025). These features quantify structural and perceptual properties of visual output, including contrast, symmetry, complexity, fractal organization, and frequency-domain characteristics, and are grounded in established work on visual aesthetics and perceptual organization (Redies, 2015).

Participants completed a cue-based drawing task using different pre-printed line stimuli, enabling the examination of both between-group differences and within-subject effects across drawing conditions. Multivariate analyses, feature-level mixed ANOVAs, dimensionality reduction via PCA, and exploratory machine-learning classification were applied to characterize group-related patterns in the structural image features extracted from the drawings.

Across analyses, drawings produced by individuals with PD differed reliably from those of HC across several structural image features. Multivariate and feature-level results indicated that PD drawings were characterized by reduced symmetry and altered global organization, alongside changes in fractal and frequency-based properties. Within-subject cue effects were present but generally smaller than group effects. PCA further revealed that group differences were concentrated in specific latent components related to global symmetry and multiscale structure, whereas other components remained largely preserved. Finally, machine-learning analyses demonstrated that a subset of computational image features carried predictive information about group membership, although substantial overlap between PD and HC drawings remained.

Taken together, these findings suggest that PD selectively affects particular structural and perceptual aspects of drawing behavior rather than causing a uniform degradation of visual output. The following sections first interpret the PCA-derived structural components before turning to feature-level effects and predictive modeling.

5.2. Interpretation of PCA findings

PCA provided a compact and interpretable representation of the multidimensional structural image feature space, revealing four principal components that together captured a substantial proportion of variance in the dataset (Greenacre et al., 2022). Importantly, PCA does not identify which specific features drive group differences or how task conditions modulate them. For this reason, PCA findings were complemented by feature-level mixed ANOVAs, allowing for a more fine-grained interpretation of component-level effects.

The four extracted components can be interpreted as follows. PC1 reflects overall visual complexity and structural density, characterized by RMS contrast, Lightness entropy, Complexity, Self-similarity, and Homogeneity, with opposing contributions from Sparseness and Balance. PC2 captures global spatial organization and symmetry, dominated by Mirror symmetry and 3D fractal dimension. PC3 contrasts local edge-orientation entropy with CNN-derived symmetry measures, reflecting algorithmically detected or local symmetry-related properties. PC4 represents spectral and multiscale spatial composition, with strong contributions from Fourier slope, Fourier sigma, 2D fractal dimension, and spatial distribution metrics.

Group comparisons revealed that not all principal components were equally sensitive to PD–related differences. Significant group effects emerged for PC2 and PC4, whereas PC1 and PC3 did not differentiate between PD and HC participants. Reduced PC2 scores in the PD group indicate impairments in global symmetry and spatial organization, driven primarily by Mirror symmetry and 3D fractal structure, suggesting altered visuospatial integration and planning. In contrast, elevated PC4 scores reflect changes in frequency-based and multiscale structure, including Fourier-based measures, two-dimensional fractal properties, and vertical spatial distribution as indexed by DCM-y-position, pointing to altered textural organization and spatial composition in PD drawings. The absence of group differences in PC1 and PC3 suggests that overall visual complexity and locally or algorithmically derived symmetry measures remain relatively preserved, underscoring the value of PCA in isolating disease-relevant structural image dimensions from those largely unaffected by diagnosis.

The components differentiating PD and HC likely reflect an interaction between motor and perceptual–cognitive processes rather than a single underlying mechanism. Producing globally symmetric and well-organized compositions require sustained visuospatial monitoring and coordinated motor execution, which may be compromised in PD. Conversely, alterations

in frequency-domain and fractal properties may reflect increased motor variability, tremor, or compensatory drawing strategies, leading to changes in fine-grained texture and spatial frequency distributions. While these interpretations remain inferential, they are consistent with known motor and visuospatial challenges associated with PD and with prior work linking Fourier- and fractal-based image statistics to fundamental principles of visual structure (Graham & Redies, 2010).

5.3. Interpretation of feature-level (mixed ANOVA) findings

At the level of individual computational image features, mixed ANOVA analyses revealed a coherent pattern of group differences that complemented both the multivariate and PCA results. Across drawing conditions, participants with PD produced images with lower RMS contrast, reduced Edge density, diminished Mirror symmetry, and altered fractal and Fourier-based properties compared to HC participants. Collectively, these findings indicate that drawings by individuals with PD were characterized by reduced structural organization and altered textural composition.

This pattern can be interpreted in light of both motor and visuospatial–cognitive mechanisms associated with PD. Reduced RMS contrast and Edge density likely reflect limitations in fine motor control, such as bradykinesia and rigidity, which constrain the precision and variability of line production (Abusrair et al., 2022; Bologna et al., 2020; Moustafa et al., 2016). Tremor and increased motor noise may further disrupt the accumulation of sharp edges and high-frequency detail, resulting in smoother and less differentiated visual patterns.

Beyond motor execution, diminished symmetry and altered fractal characteristics point to changes in spatial planning and global organization. Producing balanced and symmetric compositions requires the integration of perceptual monitoring with anticipatory motor planning, processes that are frequently impaired in PD (Ghazi-Saidi, 2020; Oliveira et al., 2025). Alterations in Fourier-based measures further suggest that PD affects how visual information is distributed across spatial scales, consistent with prior work linking such statistics to perceptual organization and early visual processing (Graham & Redies, 2010; Nieto-Escamez et al., 2023).

Importantly, although several features were sensitive to the type of drawing cue, these within-subject effects were secondary to the primary group differences. The consistency of

PD–HC differences across cue conditions indicates that the observed structural alterations reflect stable characteristics of drawing behavior rather than task-specific responses. Gender effects were minimal, suggesting that disease-related influences on visuomotor organization outweighed demographic factors in this sample.

5.4. Integration of PCA and repeated-measures analyses

The PCA-derived components (PC1–PC4) and the repeated-measures ANOVAs converge on a consistent account of how PD affects the structure of drawings. While the two approaches differ in their analytic focus, they reveal overlapping patterns that point to the same underlying alterations in visual output.

At the component level, group differences emerged primarily for PC2 and PC4. PC2, which captured global symmetry and structural organization, was reduced in participants with PD, aligning with feature-level findings of diminished Mirror symmetry, Balance, and Edge density in the mixed ANOVAs. PC4, defined by Fourier-based and fractal characteristics, showed elevated scores in the PD group, mirroring feature-level differences in Fourier slope, Fourier sigma, and Fractal dimension. Together, these components reflect changes in both global organization and multiscale texture, suggesting that PD affects how visual information is structured across spatial levels (Nieto-Escamez et al., 2023).

The repeated-measures analyses provide additional specificity by identifying which individual computational image features drive these component-level effects and by demonstrating their robustness across drawing cues. Lower RMS contrast, reduced Edge density, and altered fractal and Fourier properties were consistently observed in PD drawings, supporting the interpretation that both motor constraints and visuospatial planning deficits contribute to these differences (Abusrair et al., 2022; Bologna et al., 2020; Moustafa et al., 2016; Nieto-Escamez et al., 2023). Although cue-related effects and occasional interactions with gender were present, they were generally secondary to the main group effects, reinforcing the notion that the observed structural alterations represent stable characteristics of drawing behavior rather than task-dependent variations.

Taken together, the PCA and repeated-measures analyses serve complementary roles. PCA offers a dimensional summary, reducing a large set of correlated measures to a small number of interpretable latent components. In contrast, the mixed ANOVAs provide feature-

level specificity, clarifying how particular visual properties vary as a function of group and task. The fact that the same group-related patterns emerged across both approaches strengthens confidence in the robustness of the findings and supports the conclusion that PD selectively alters both the structural organization and textural complexity of artistic output. This multi-level analytical strategy provides a comprehensive and objective characterization of drawing behavior in a clinical population.

5.5. Interpretation of Machine-Learning Results

An important methodological consideration concerns the DCM-x and DCM-y features. These values were not available for the SC group due to incomplete feature extraction in the original dataset. Because gradient-boosted tree models can treat missing values as informative splits, the absence of DCM metrics may have contributed to the high separability of the SC group in the multiclass classification analysis. Consequently, the prominence of DCM-related features in the SHAP analyses, particularly for distinguishing younger participants, should be interpreted with caution.

Importantly, classification between PD and age-matched HC relied on a broader constellation of structural features, including fractal and frequency-based measures, suggesting that disease-related effects were not solely driven by DCM metrics. Nevertheless, future analyses using fully complete feature sets will be necessary to confirm the stability of DCM-related contributions and their role in group discrimination.

The machine-learning analyses demonstrated that computational image features extracted from drawings contain meaningful information for distinguishing participant groups at levels above chance. Importantly, model evaluation was conducted using conservative, group-based cross-validation procedures, ensuring that drawings from the same participant were never split across training and test sets. Such validation strategies are recommended when multiple observations per individual are present, as they reduce the risk of data leakage and inflated performance estimates (Roberts et al., 2017; Varma & Simon, 2006).

Classification performance differed substantially depending on the comparison. Distinguishing the SC group from older participants yielded near-perfect accuracy, indicating that age-related differences in drawing structure exert a strong influence on the extracted computational image features. In contrast, PD and age-matched HC exhibited substantial

overlap in drawing characteristics, and classification between these groups was moderate rather than near-perfect. This pattern is theoretically meaningful. It suggests that PD does not produce a global breakdown of visual production, but instead selectively modulates specific structural dimensions. The detected group differences therefore reflect subtle but systematic alterations rather than gross impairment.

Although the classifier did not achieve complete separation between PD and HC participants, performance remained reliably above chance. This indicates that the extracted image features contain meaningful group-level information, even if they are not sufficient for individual-level classification. Such probabilistic differentiation is consistent with the subtle and heterogeneous nature of visuomotor alterations in PD.

Model interpretation using SHAP further clarified which features contributed most strongly to classification decisions. Across analyses, features related to fractal structure, Fourier-based frequency characteristics, and spatial distribution consistently showed the largest contributions, whereas CNN-derived symmetry measures and local texture features contributed minimally. Notably, this feature importance profile closely mirrored the results of the PCA and mixed ANOVA analyses.

A particularly compelling aspect of the findings is the convergence across analytic levels. PCA, feature-level statistical tests, and machine-learning interpretation independently highlighted overlapping structural dimensions, particularly symmetry and multiscale organization, as central to group differentiation. The fact that these patterns emerged across conceptually distinct analytic strategies strengthens confidence that the results reflect meaningful properties of drawing structure rather than analytic artifacts.

5.6. Theoretical and clinical implications

The present findings contribute to theoretical accounts of visual production by demonstrating that objectively quantified image features capture meaningful aspects of visuomotor integration. Drawing is a complex activity that requires the coordination of perceptual processing, motor planning, and fine motor execution (Nazar et al., 2017). The observed group differences suggest that PD affects not only motor output but also the organization of visual structure at multiple spatial scales. In this context, computational image features provide a principled framework for linking motor constraints with perceptual structure in produced images.

From a theoretical perspective, the results support the view that motor impairments can manifest as systematic changes in visual organization rather than merely increased noise or reduced executional precision. Alterations in symmetry, contrast, and multiscale texture suggest that Parkinson's-related changes extend beyond line instability to affect higher-order structural properties of drawings. These findings are consistent with models of PD that emphasize disrupted sensorimotor integration and reduced flexibility in planning and executing complex actions. Importantly, the preservation of some structural dimensions alongside selective impairments underscores that visuomotor changes in PD are not uniform but dimension-specific.

From a clinical standpoint, the results highlight the potential of drawing-based tasks combined with computational feature extraction as sensitive tools for characterizing subtle visuomotor alterations. Because drawing is non-invasive, low-cost, and easy to administer, it represents a promising complement to established neuropsychological and motor assessments (D'Alessandro, 2024). The convergence between inferential statistical analyses and machine learning results further suggests that objectively measured image features capture clinically relevant variance that may not be readily apparent through visual inspection alone.

At the same time, these findings must be interpreted with appropriate caution. Although group-level differences were robust and consistent across analytic approaches, substantial overlap between individuals with PD and HC was observed at the individual level. This partial overlap is not unexpected. PD does not produce uniform visuomotor disruption but rather subtle, dimension-specific alterations that vary across individuals and disease stages. Accordingly, the extracted image features should not be understood as deterministic markers, but as probabilistic indicators of structural differences in visual production. Rather than functioning as standalone diagnostic tools, computational image features may be most informative when embedded within broader assessment frameworks, potentially contributing to multidimensional characterization or longitudinal monitoring of visuomotor change. Future research using larger samples and longitudinal designs will be necessary to determine the stability of these effects and their sensitivity to disease progression.

5.7. Limitations

Several limitations of the present study should be acknowledged. First, the study did not assess creativity as a psychological construct, nor was it designed to do so. Consequently, no conclusions can be drawn regarding creative ability or creative perception in PD. Although creative drawing tasks were used, the analyses focused exclusively on objective, image-based features of the produced drawings rather than subjective evaluations or creative intent. As such, the findings pertain to visuomotor and perceptual characteristics of visual output, not to creativity per se.

Second, the sample size was relatively modest, particularly in light of the high dimensionality of the extracted feature space. Although multivariate and machine learning methods were applied with appropriate safeguards, including dimensionality reduction and conservative cross-validation, the results should be interpreted with caution. In addition, the PD cohort was collected independently by a collaborating research group at the Expertise Centre for Parkinson and Movement Disorders, Radboud University Medal Center, Nijmegen, the Netherlands. Although task instructions and image analysis procedures were standardized, cultural, educational, or healthcare-related differences may influence drawing behavior and disease characteristics. Together, these factors may limit the generalizability of the findings, underscoring the importance of replication in larger and cross-cultural samples.

Third, the cross-sectional design of the study limits inferences about disease progression or causal mechanisms. The observed group differences reflect between-group variation at a single time point and cannot determine whether the identified features change systematically over the course of PD. Longitudinal designs would be required to assess sensitivity to disease progression or treatment-related changes.

Fourth, computational image features do not directly correspond to subjective aesthetic or creative experience. While objective metrics such as symmetry, contrast, and fractal dimension capture measurable properties of visual structure, they may not fully reflect how drawings are perceived or evaluated by human observers. Future work combining computational analyses with subjective ratings or behavioral measures could provide a more comprehensive account of aesthetic perception and production (Redies et al., 2015).

Finally, the machine learning analyses were conducted externally by an independent collaborator using established and transparent procedures. While this ensured methodological rigor and appropriate cross-validation, it limited direct control over model development and

parameter tuning within the present work. Nevertheless, all analyses were fully documented, and the convergence between machine learning results and inferential statistical findings supports the validity of the conclusions drawn.

5.8. Future Directions

The findings of the present study point to several important directions for future research. First, longitudinal designs will be essential to determine whether the identified features are sensitive to disease progression in PD. Repeated drawing assessments over time could clarify whether changes in symmetry, fractal structure, and frequency-based image properties evolve systematically with disease severity or treatment status, thereby increasing their potential clinical relevance.

Second, future studies should aim to disentangle motor and perceptual–cognitive contributions to the observed drawing differences. Combining computational analysis of drawings with independent measures of motor function, visuospatial ability, and perceptual sensitivity would help clarify the mechanisms underlying alterations in image structure. Such multimodal approaches could determine whether changes in drawing structure primarily reflect motor execution constraints, altered visuospatial planning, or their interaction.

Third, larger and more diverse samples would improve the generalizability of the findings. Increasing sample size would allow for more robust machine-learning models, enable subgroup analyses (e.g., disease stage, medication status), and support more stable estimation of multivariate effects. Replication across independent cohorts and cultural contexts would further strengthen confidence in the robustness of the identified computational image markers.

Fourth, future work could integrate subjective aesthetic judgments with computational measures. While the present study focused on objective image properties, combining these with human ratings of aesthetics, structure, or expressiveness could help bridge the gap between measurable visual features and perceptual experience. This integration may clarify which computational features are most relevant for human observers and aesthetic evaluation.

Finally, the methodological framework applied here could be extended beyond PD to other neurological or psychiatric conditions.

5.9. Conclusion

The present study demonstrates that drawings produced by individuals with PD differ systematically from those of HC in their objective image structure. Using computational image analysis in combination with multivariate statistics and interpretable machine-learning methods, the analyses revealed selective alterations in contrast, symmetry, and multiscale structural properties. These differences are consistent with changes in visuomotor organization rather than a general decline in drawing ability.

The findings show that drawing-based tasks, when analyzed using objective computational measures, are sensitive to subtle but reliable differences in visual production associated with neurological conditions. By integrating dimensionality reduction, feature-level statistical analyses, and predictive modeling, the study provides a multi-level framework for characterizing how motor and perceptual processes jointly shape visual output.

Overall, this work demonstrates the value of computational image-based analysis as a rigorous and reproducible framework for investigating complex visuomotor behavior. By moving beyond subjective evaluation, objective structural features offer a principled method to characterize subtle, disease-related alterations in visual production that may remain undetected through conventional clinical or perceptual assessment.

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Appendix 1

Group Means and Standard Deviations for Computational Image Features Showing Significant Group Differences

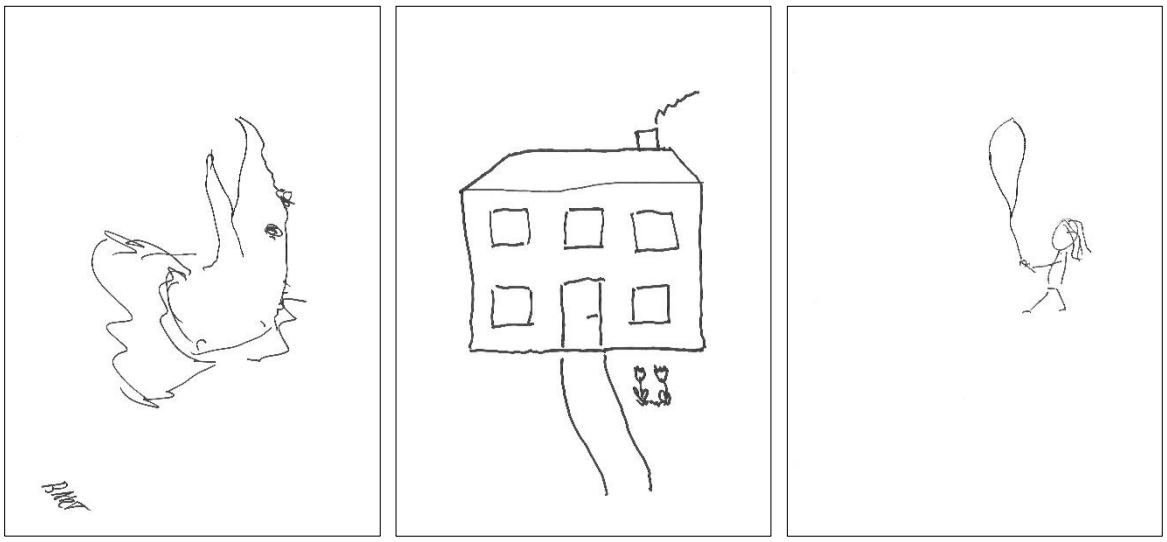
Feature	HC Mean (SD)	PD Mean (SD)
RMS contrast	13.94 (3.41)	12.22 (3.10)
Edge density	74.01 (34.61)	60.19 (27.49)
Mirror symmetry	0.56 (0.54)	0.37 (0.31)
DCM y position	0.08 (0.20)	−0.01 (0.16)
Fourier slope	−1.82 (0.16)	−1.65 (0.20)
Fourier sigma	0.09 (0.04)	0.06 (0.04)
2D fractal dimension	1.32 (0.05)	1.34 (0.05)
3D fractal dimension	2.40 (0.07)	2.37 (0.07)

Note. Values represent means averaged across cue conditions. For Fourier slope, less negative values indicate a shallower slope.

Appendix 2

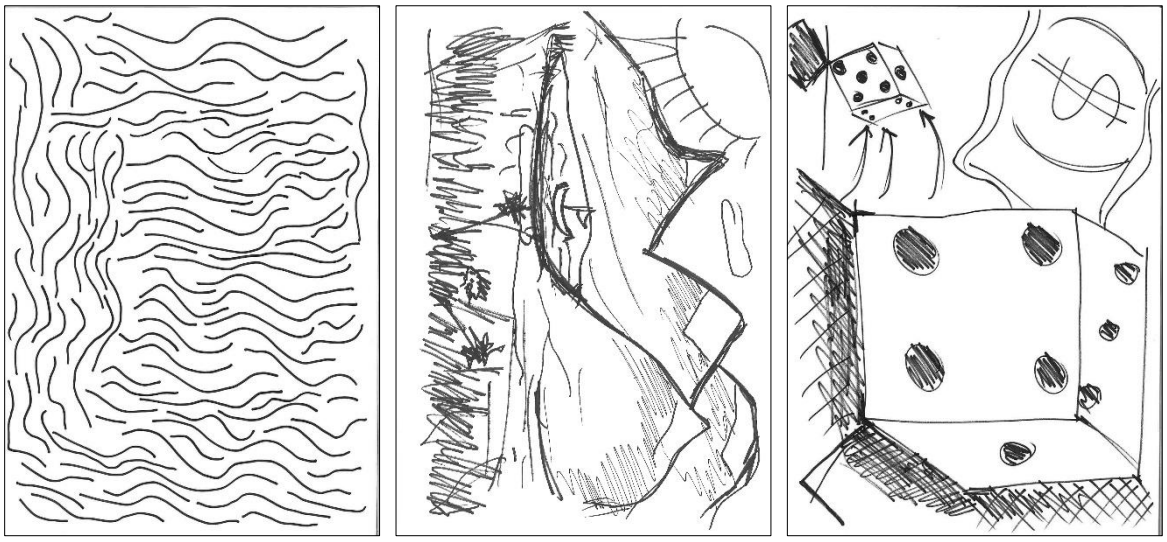
Representative Drawings for Computational Image Features

Low in RMS contrast



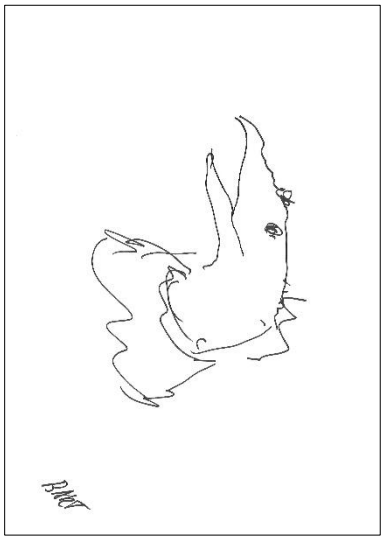
PD (3.32) HC (3.77) PD (4.59)

High in RMS contrast

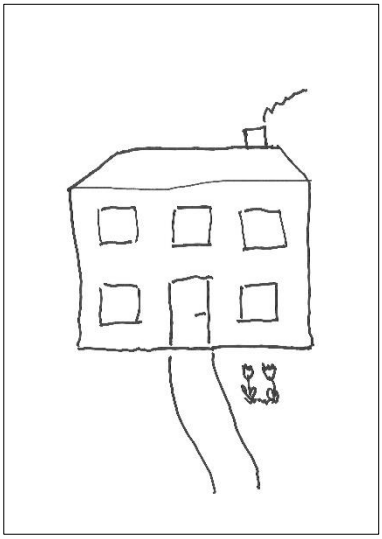


SC (25.20) HC (25.06) SC (24.68)

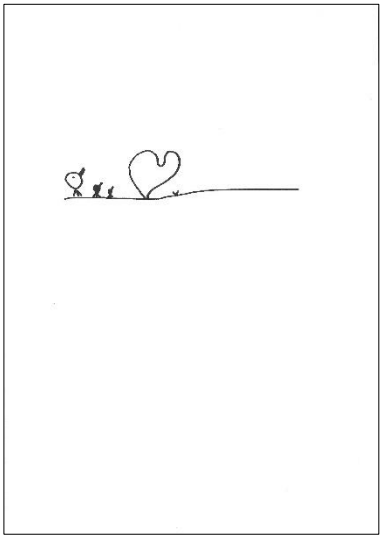
Low in Lightness entropy



PD (0.05)

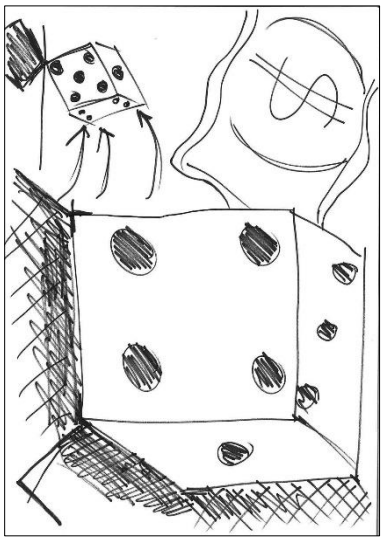


HC (0.08)



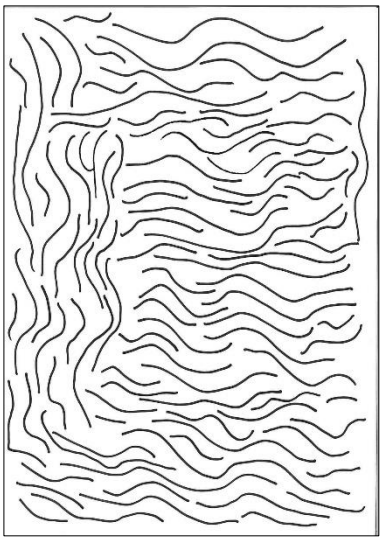
PD (0.11)

High in Lightness entropy



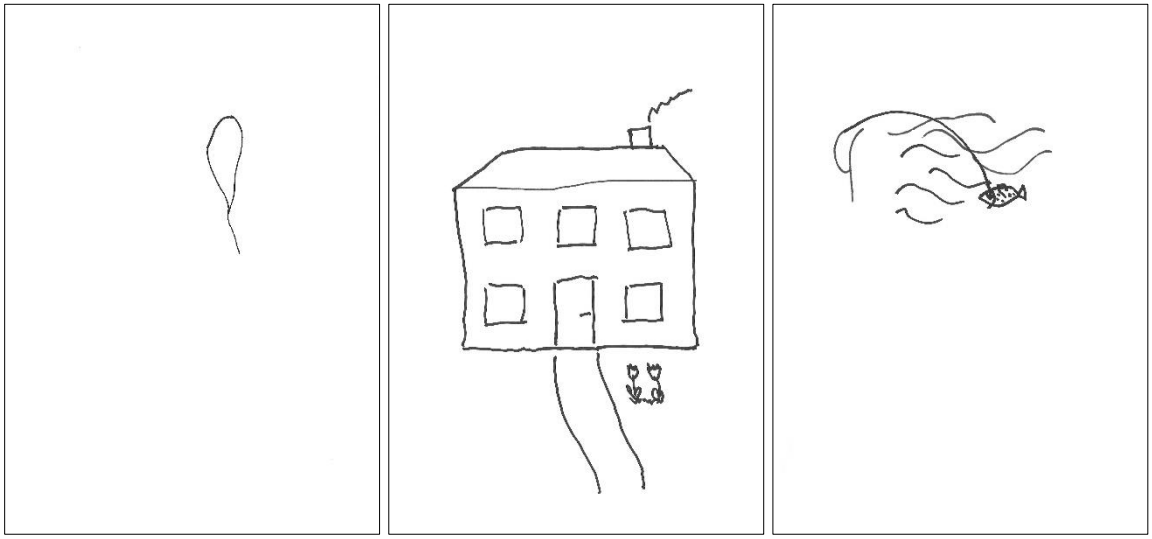
SC (2.89)

SC (2.79)



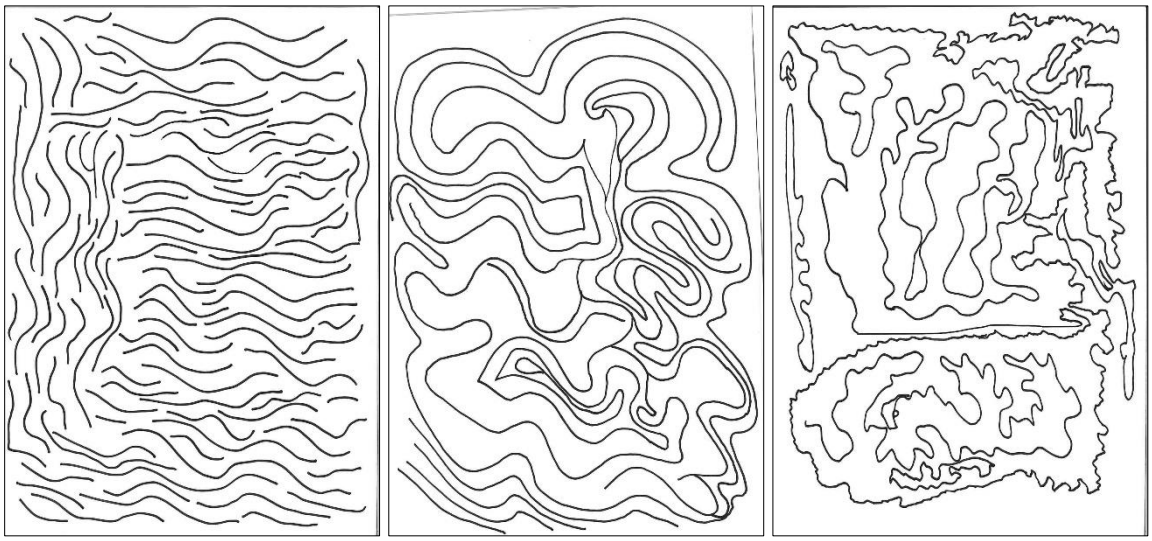
SC (2.90)

Low in Complexity



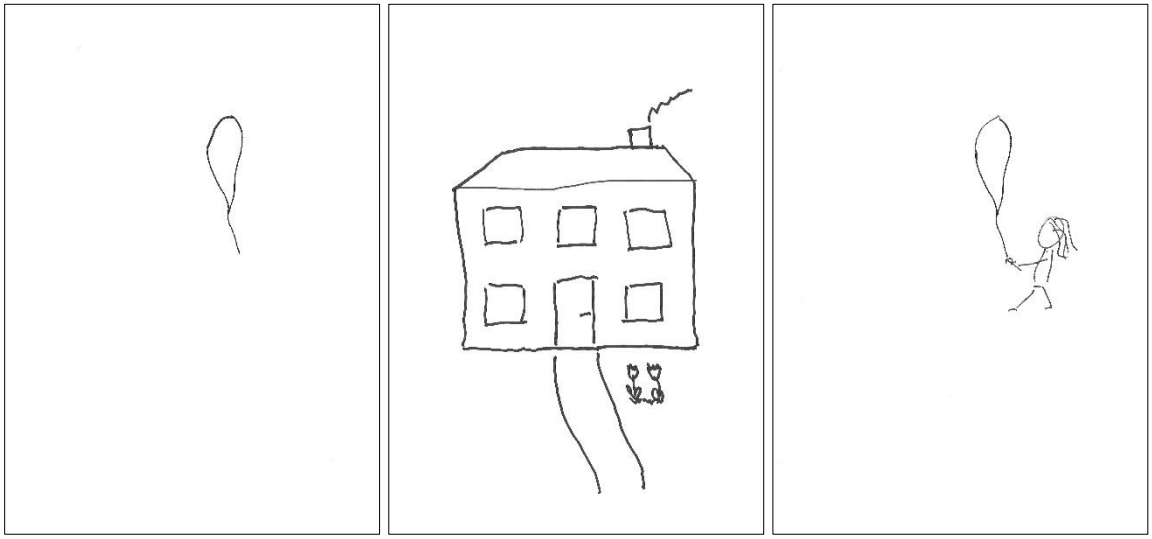
PD (0.12) HC (0.13) HC (0.20)

High in Complexity



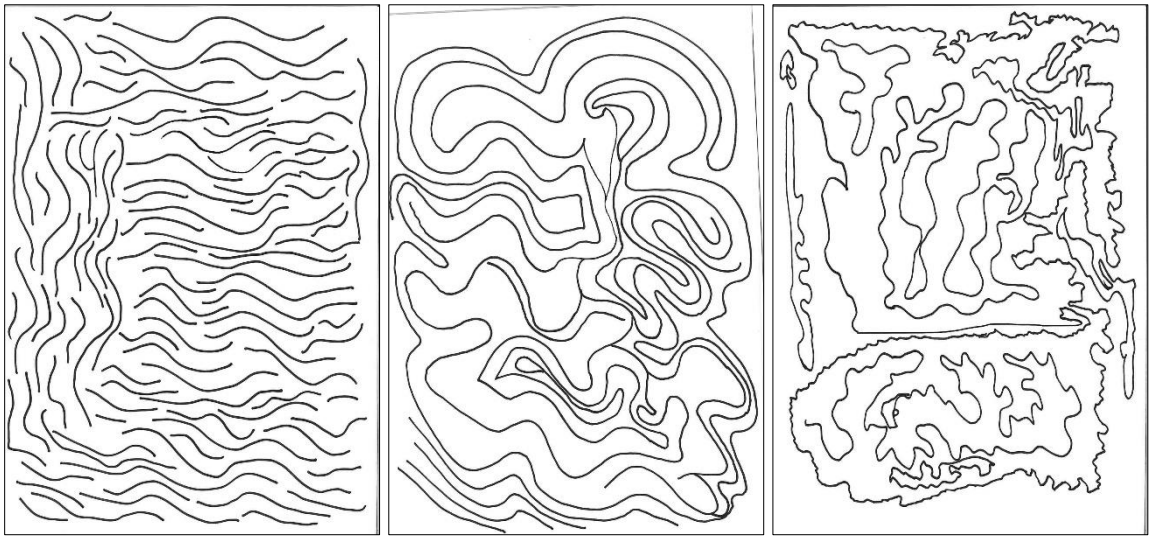
SC (23.63) SC (20.74) SC (18.27)

Low in Edge density



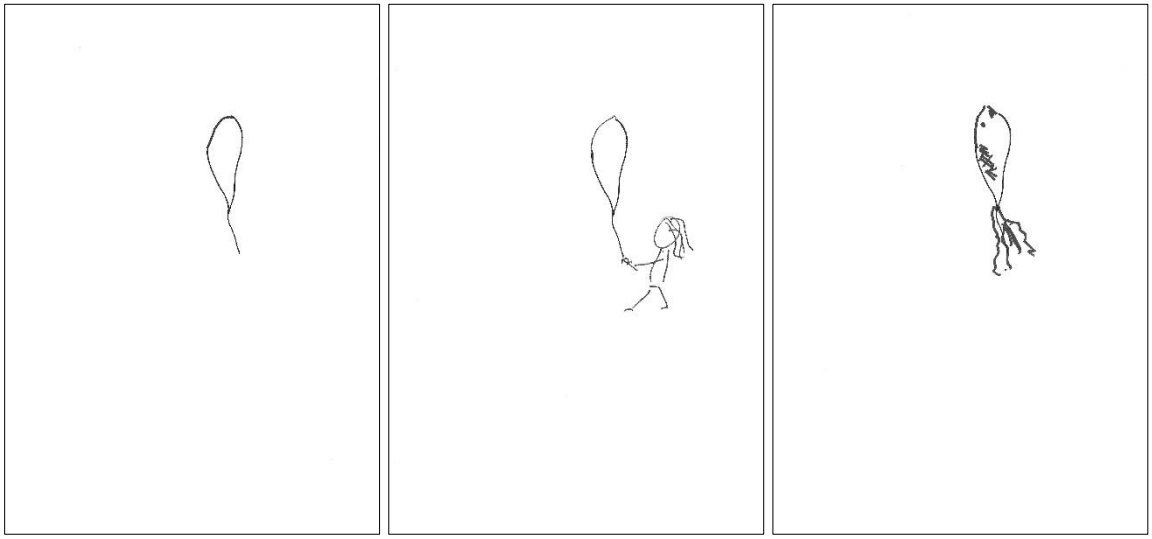
PD (4.16) HC (5.70) PD (7.96)

High in Edge density



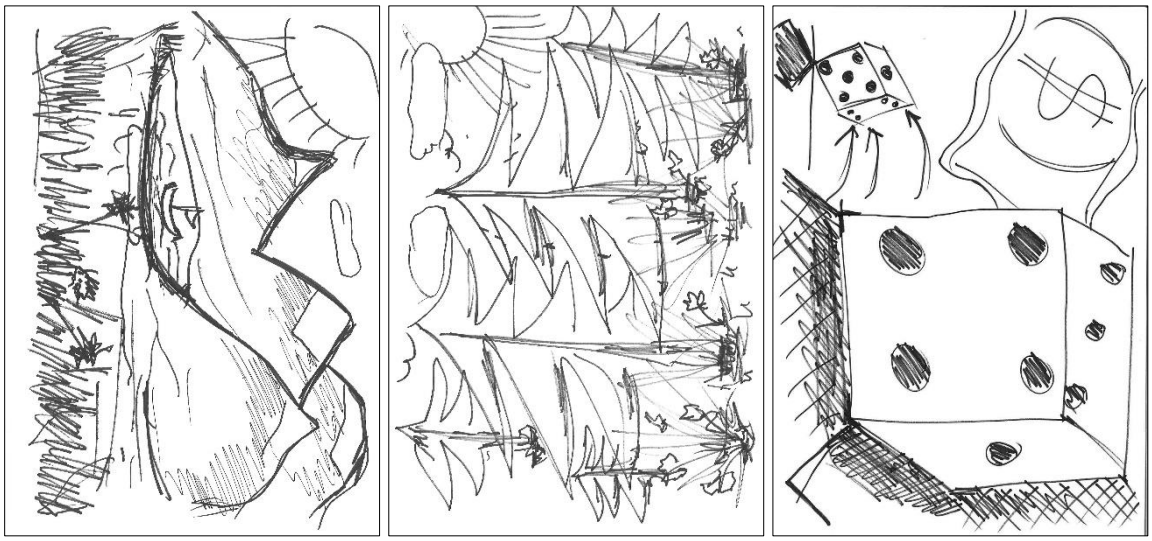
SC (275.29) SC (228.21) SC (201.68)

Low in Mirror symmetry



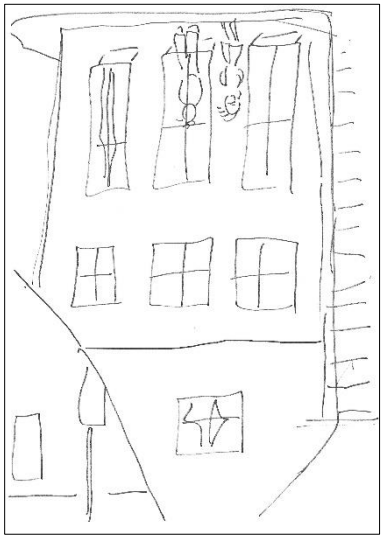
PD (0) PD (0.01) PD (0.01)

High in Mirror symmetry

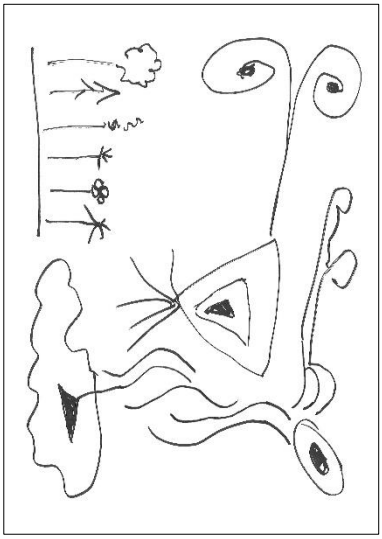


HC (4.39) HC (3.28) SC (2.88)

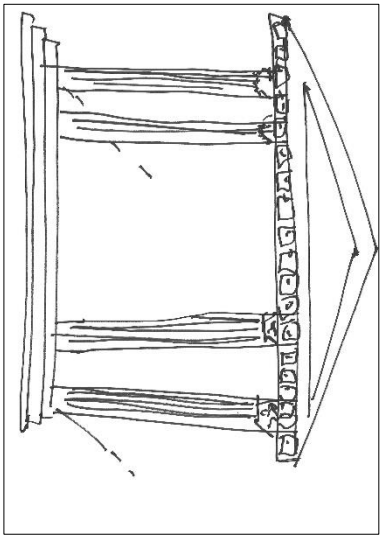
Low in Balance



PD (7.61)

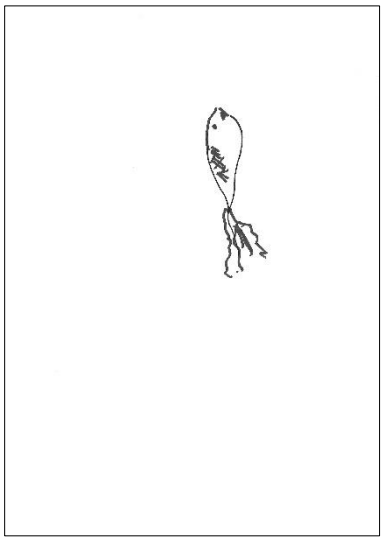


HC (9.40)

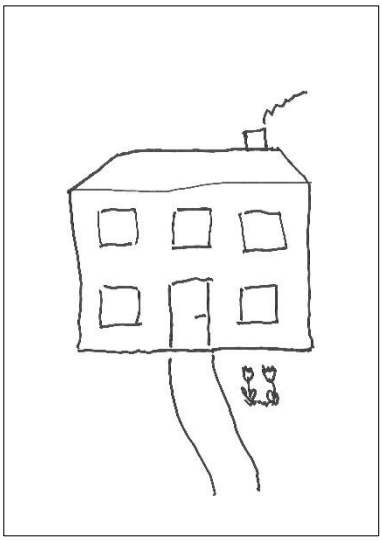


HC (9.47)

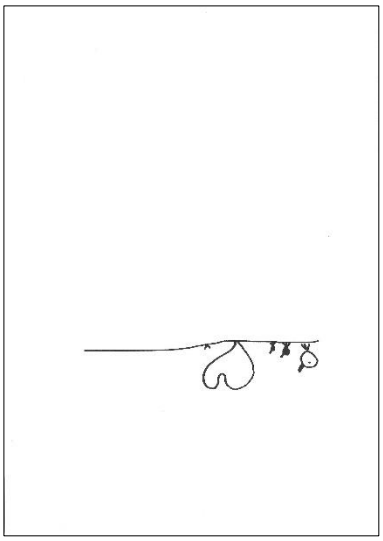
High in Balance



PD (81.70)

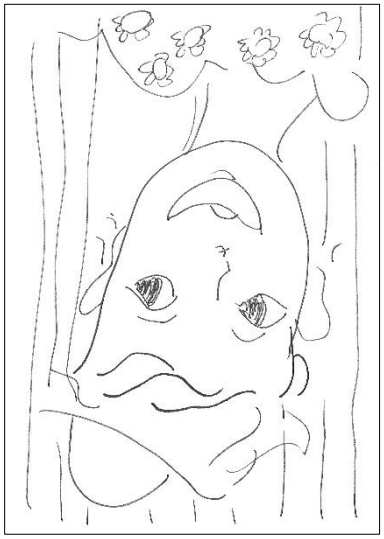


HC (77.94)

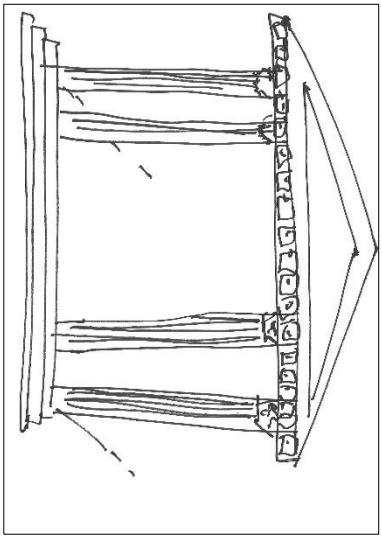


PD (77.87)

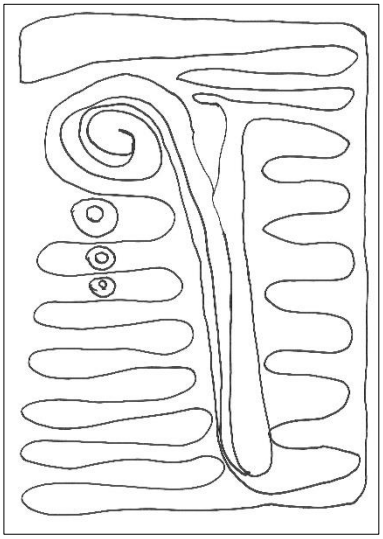
Low in DCM distance



PD (0.84)

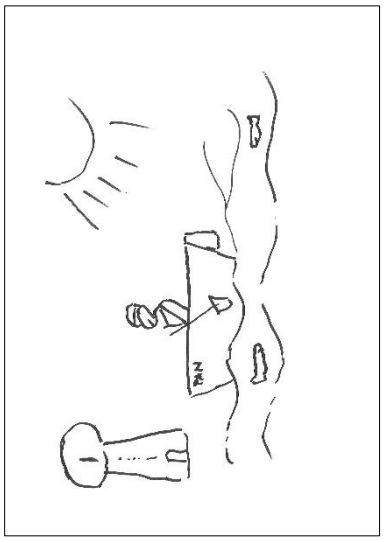


HC (0.97)



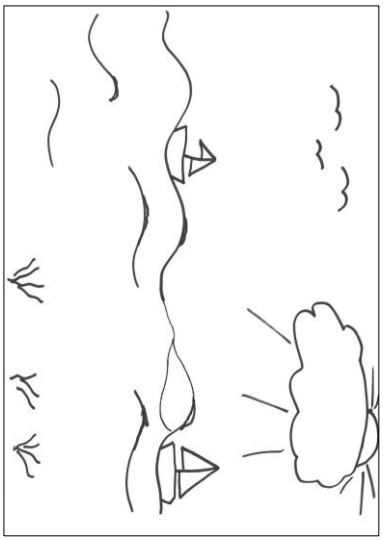
HC (0.16)

High in DCM distance



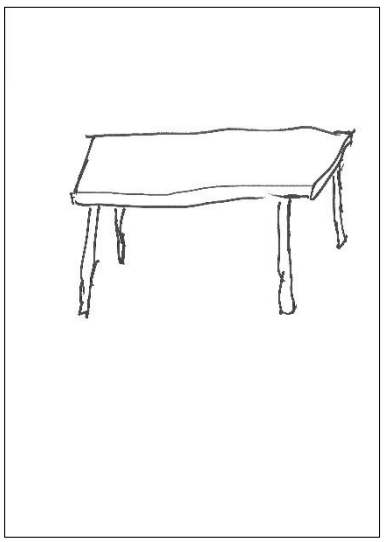
HC (64.65)

HC (60.84)

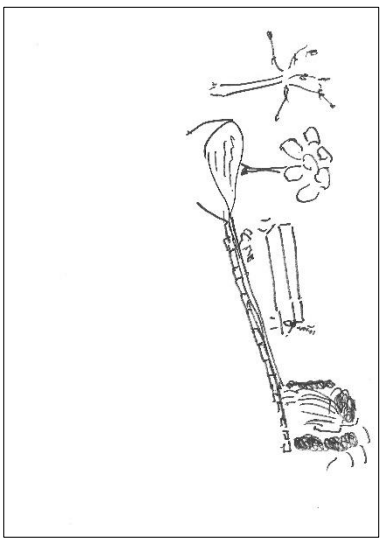


HC (56.13)

Low in DCM-x-position



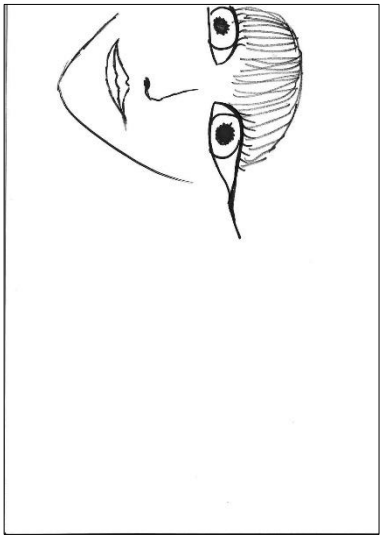
HC (-0.25)



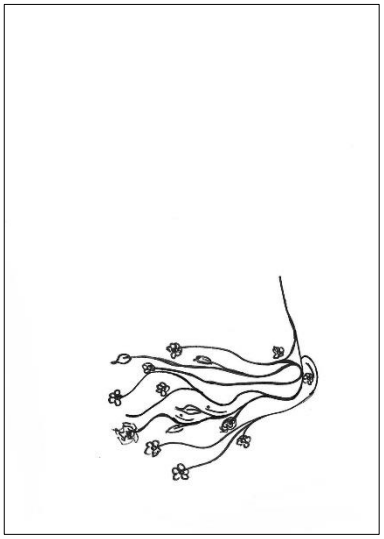
PD (-0.24)

SC (-0.23)

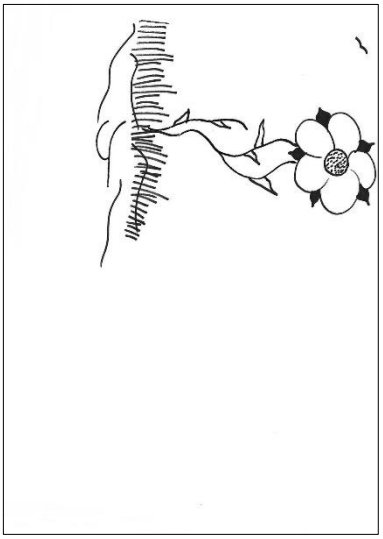
High in DCM-x-position



SC (0.26)

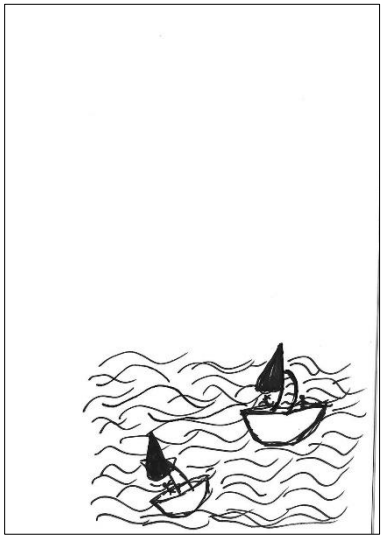


SC (0.24)

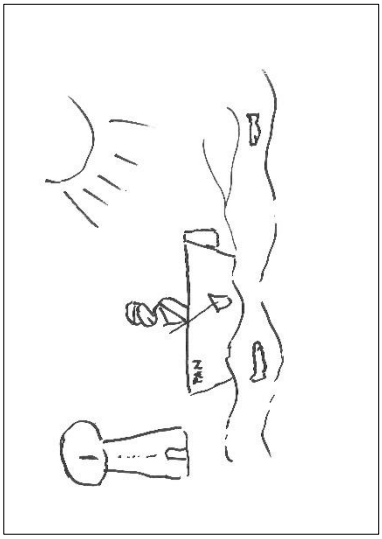


SC (0.23)

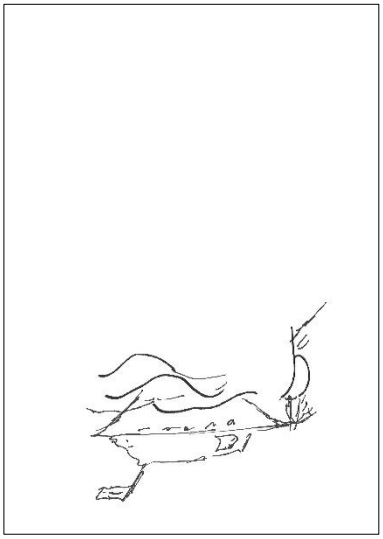
Low in DCM-y-position



SC (-0.31)



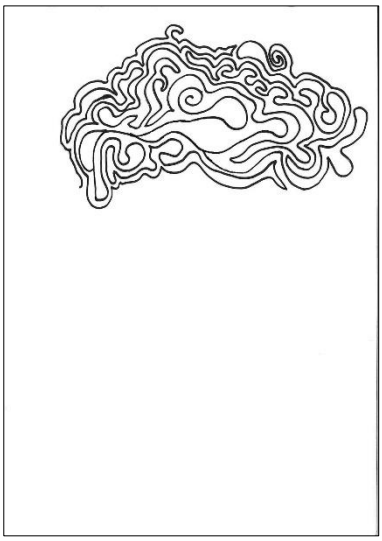
HC (-028)



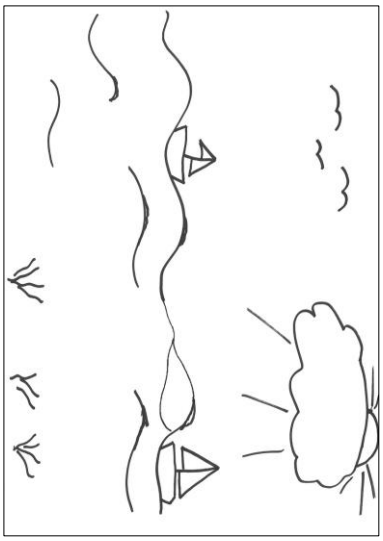
PD (-0.27)

High in DCM-y-position

HC (0.29)

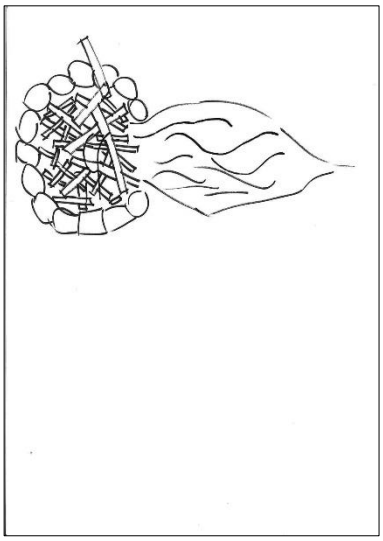


SC (0.28)



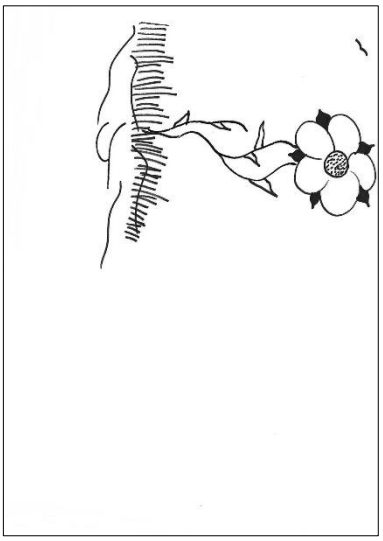
SC (0.27)

Low in CNN symmetry left-right



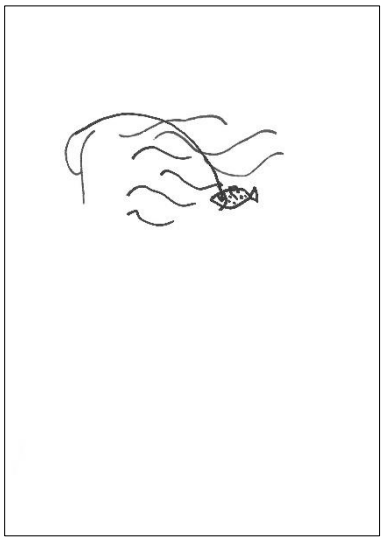
SC (0.11)

SC (0.11)

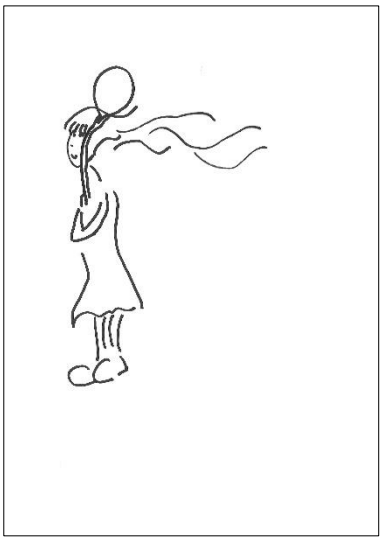


SC (0.11)

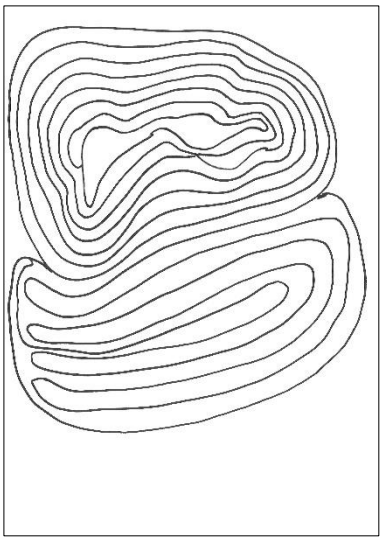
High in CNN symmetry left-right



HC (0.72)



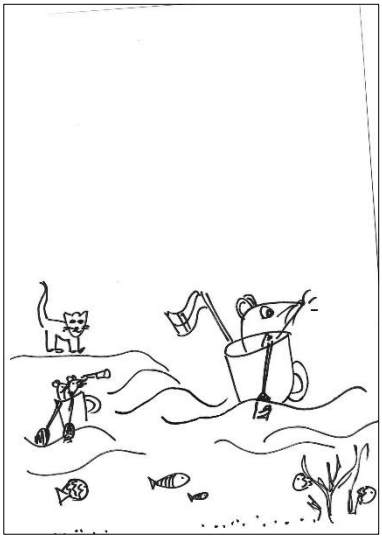
HC (0.70)



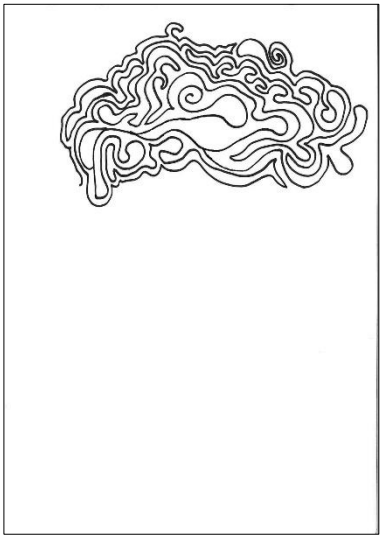
HC (0.70)

Low in CNN symmetry up-down

SC (0.07)

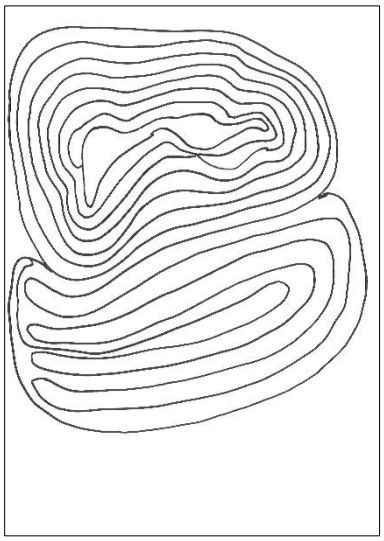


SC (0.08)

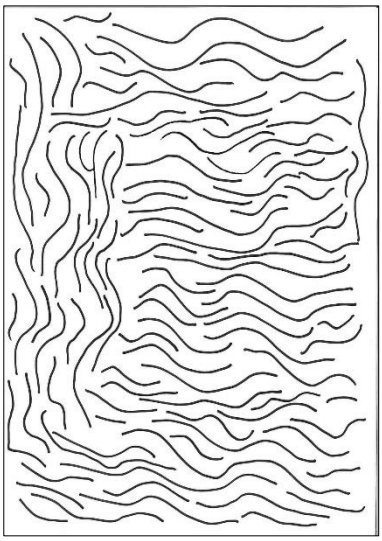


SC (0.08)

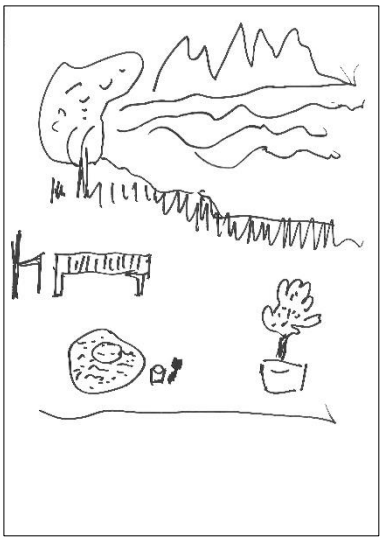
High in CNN symmetry up-down



HC (0.64)

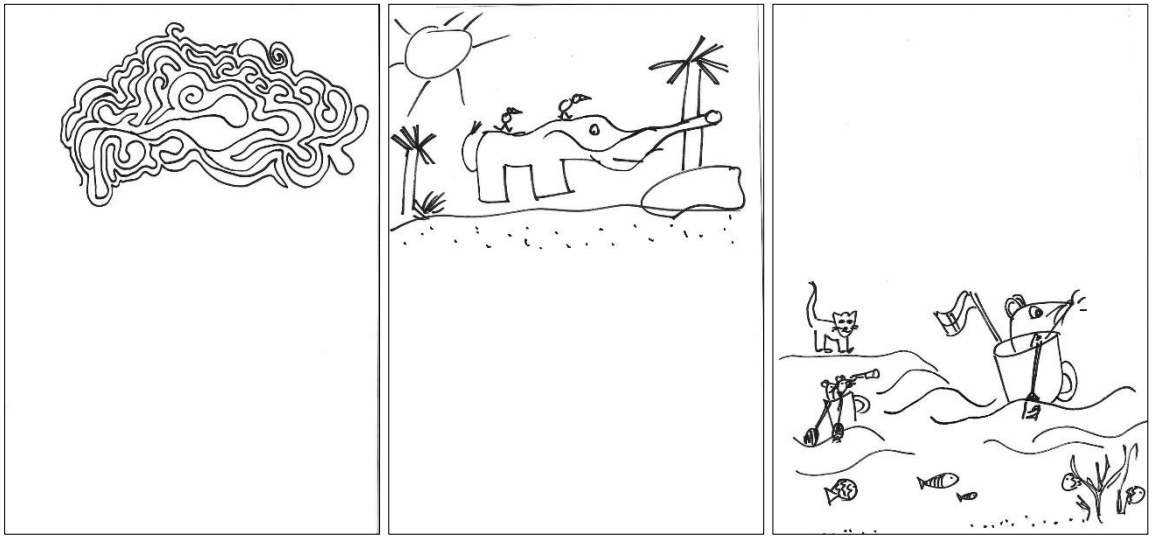


SC (0.63)



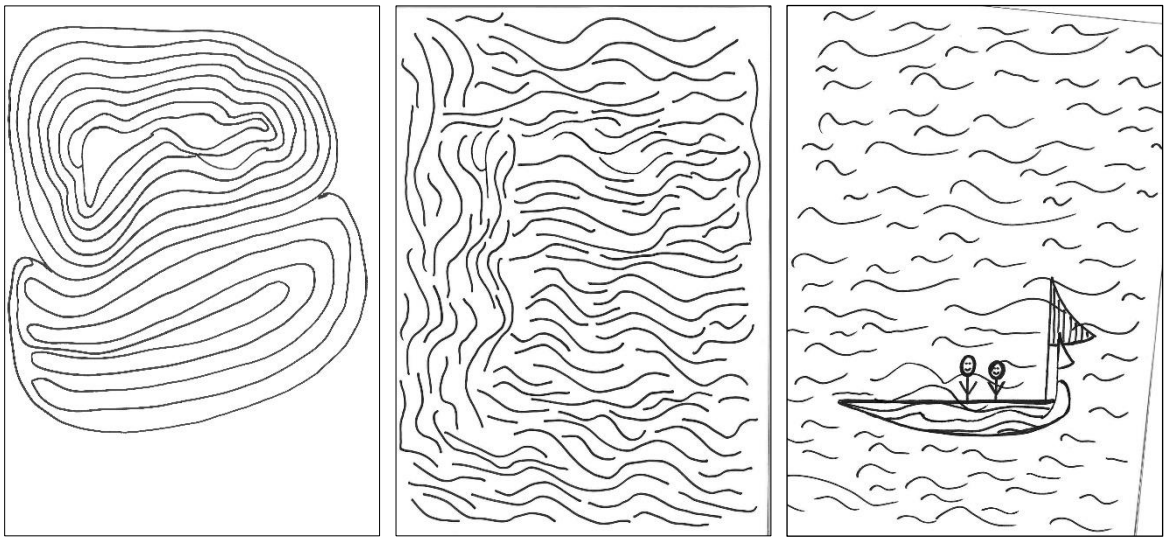
HC (0.57)

Low in CNN symmetry left-right & up-down



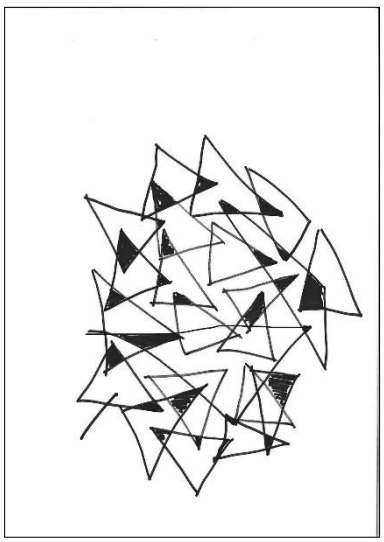
SC (0.08) SC (0.08) SC (0.78)

High in CNN symmetry left-right & up-down

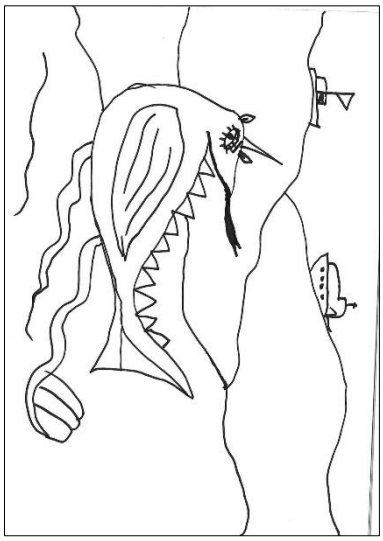


HC (0.67) SC (0.56) SC (0.55)

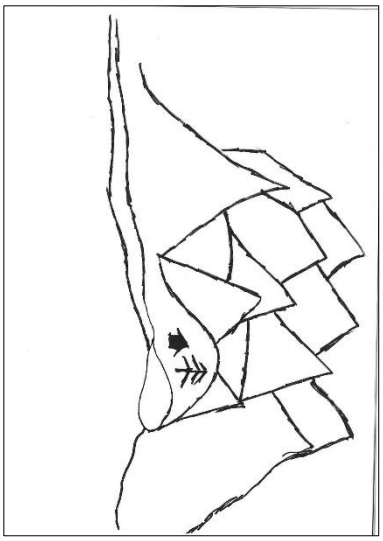
Low in Fourier slope



SC (-2.76)

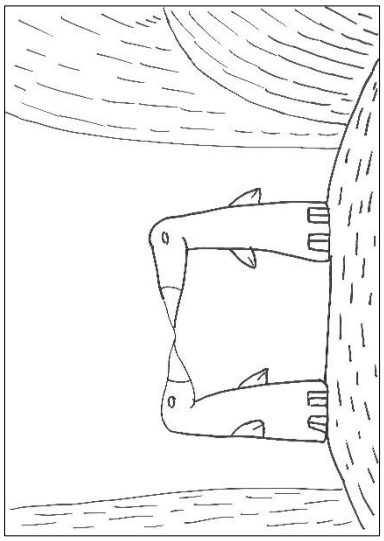


SC (-2.71)

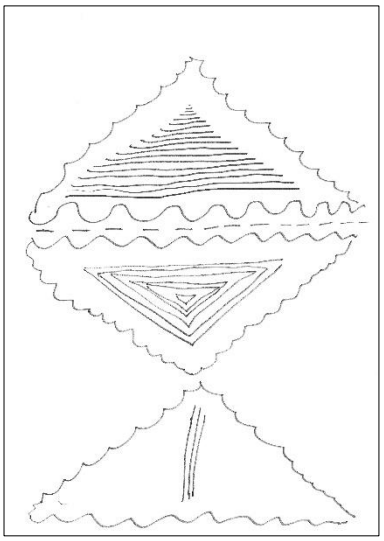


SC (-2.67)

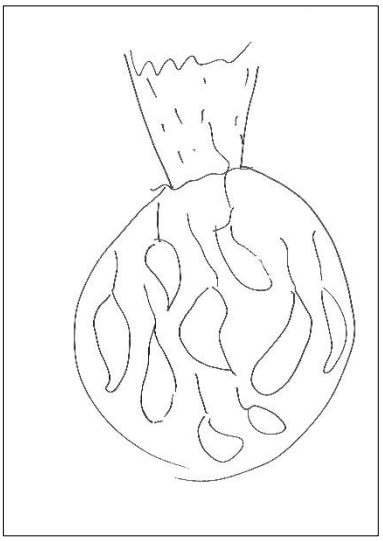
High in Fourier slope



HC (-1.23)

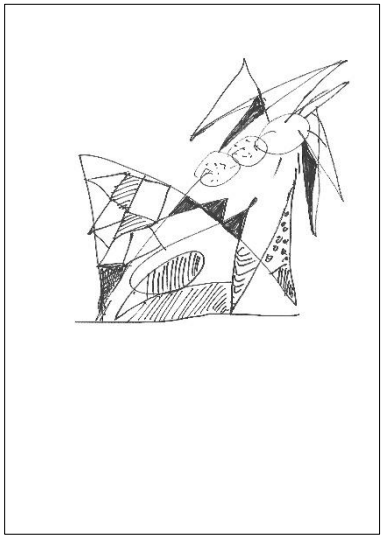


PD (-1.23)

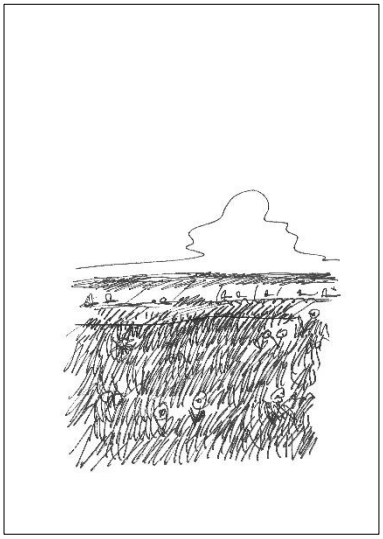


PD (-1.25)

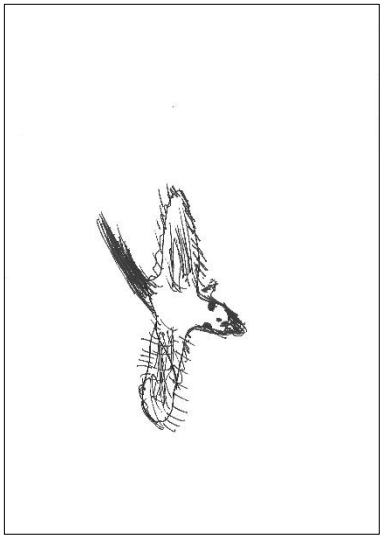
Low in Fourier sigma



HC (0.00274)

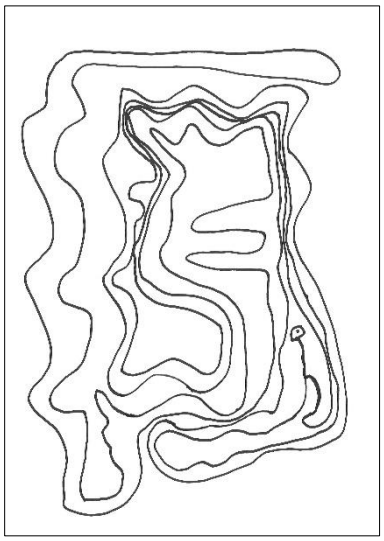


HC (0.00364)

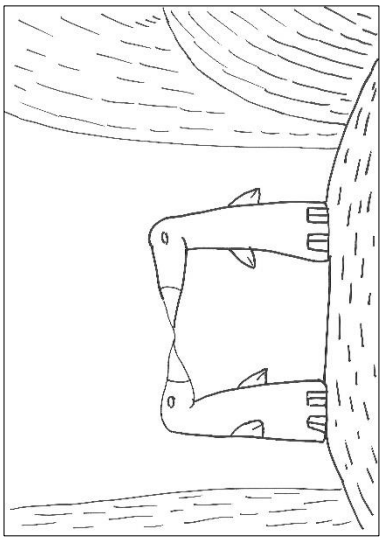


PD (0.00537)

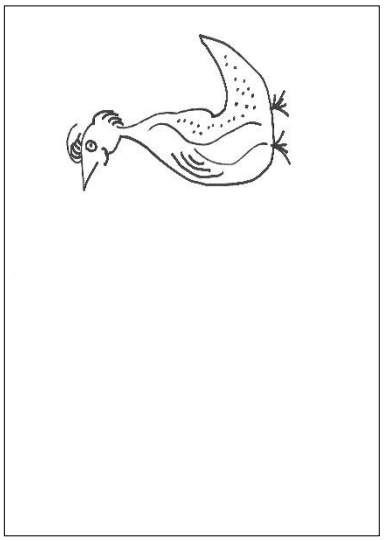
High in Fourier sigma



HC (0.32)

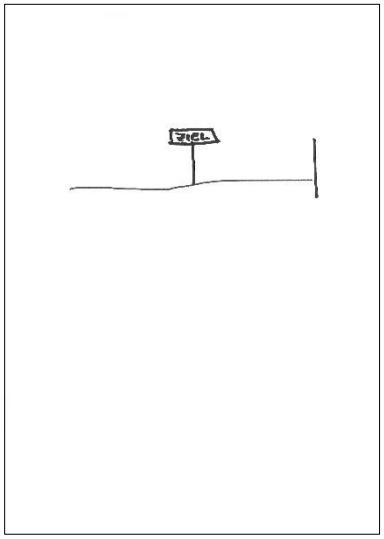


HC (0.30)

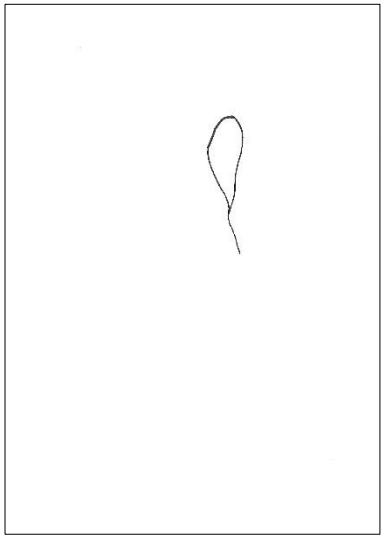


HC (0.22)

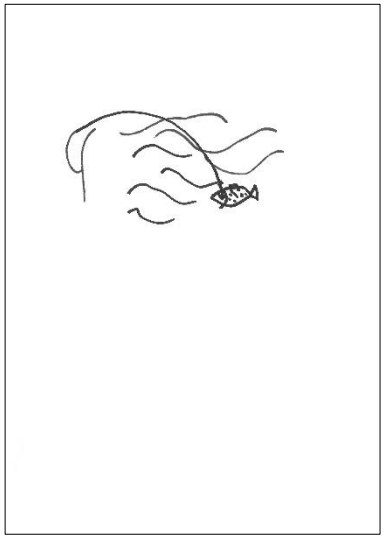
Low in 2D fractal dimension



HC (1.07)



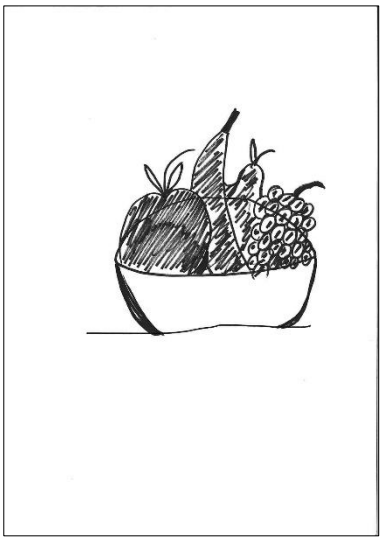
PD (1.09)



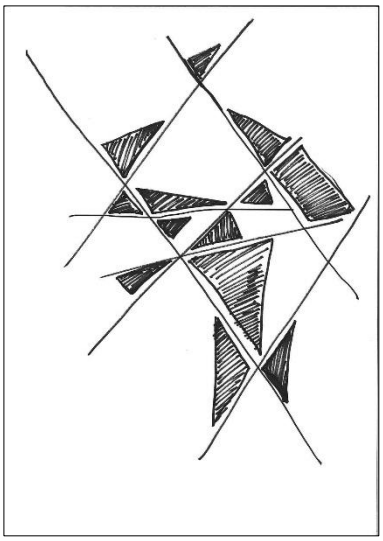
HC (1.15)

High in 2D fractal dimension

SC (2.73)



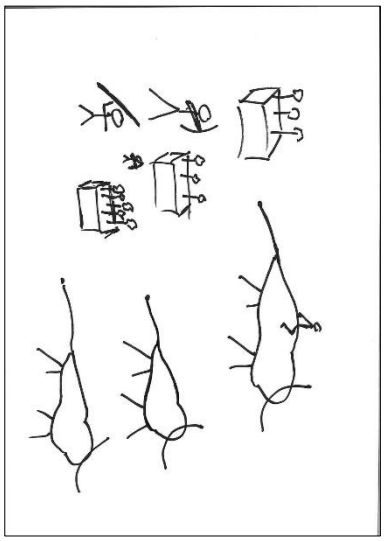
SC (2.71)



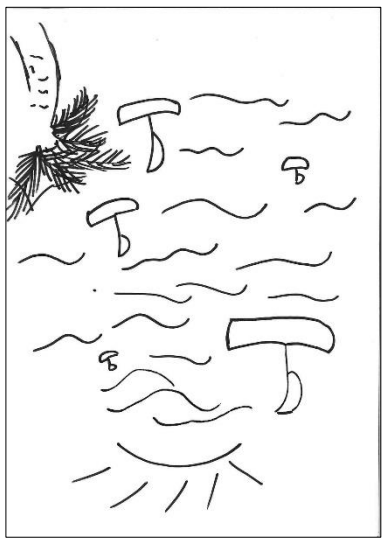
SC (2.69)

Low in 3D fractal dimension

SC (1.25)

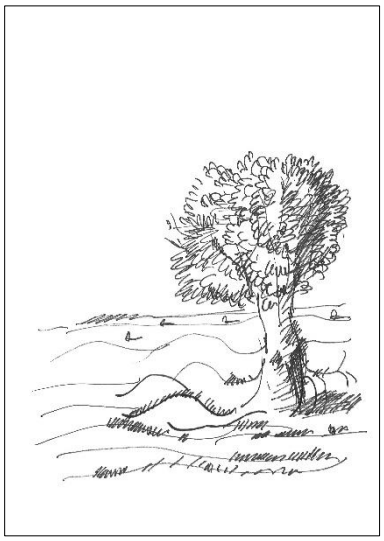


SC (1.25)

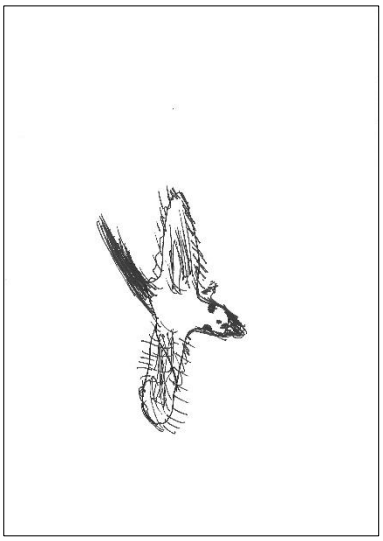


SC (1.26)

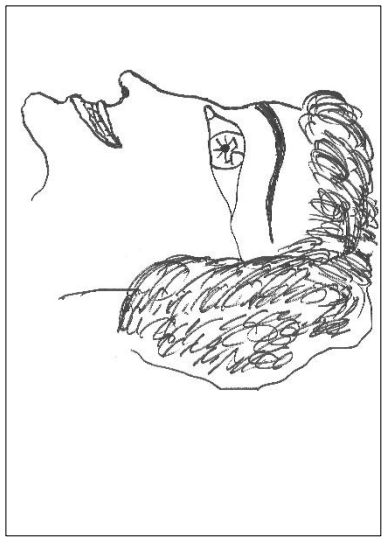
High in 3D fractal dimension



HC (2.82)

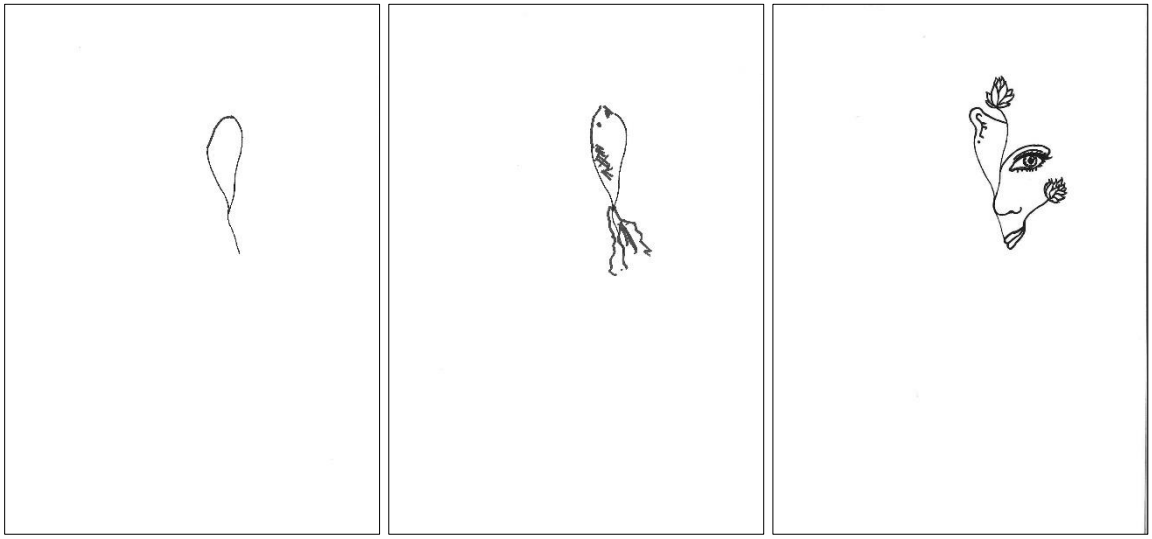


PD (2.67)



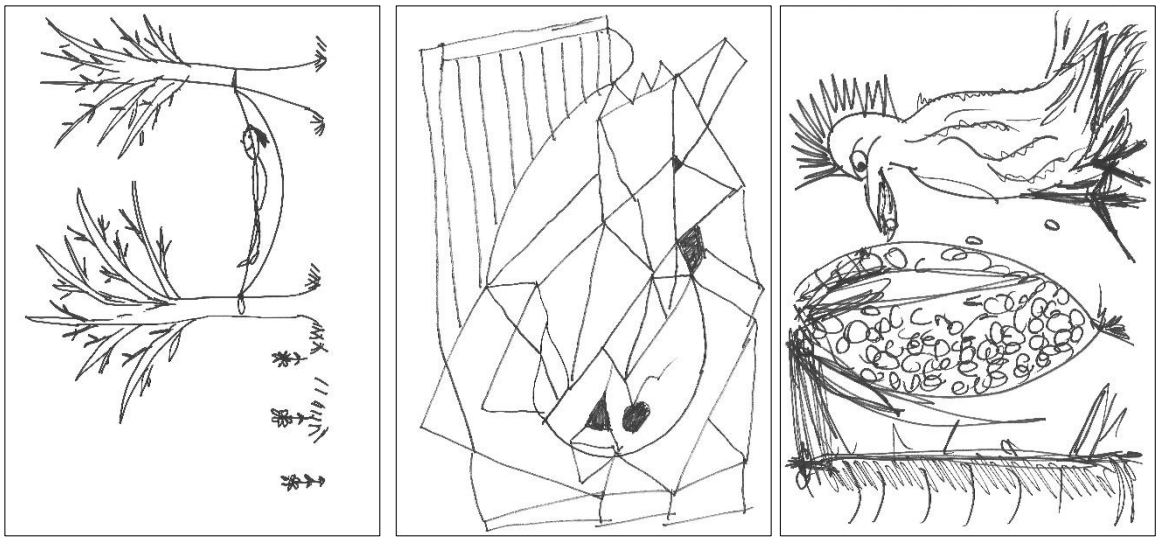
PD (2.64)

Low in Self-similarity (PHOG-based)



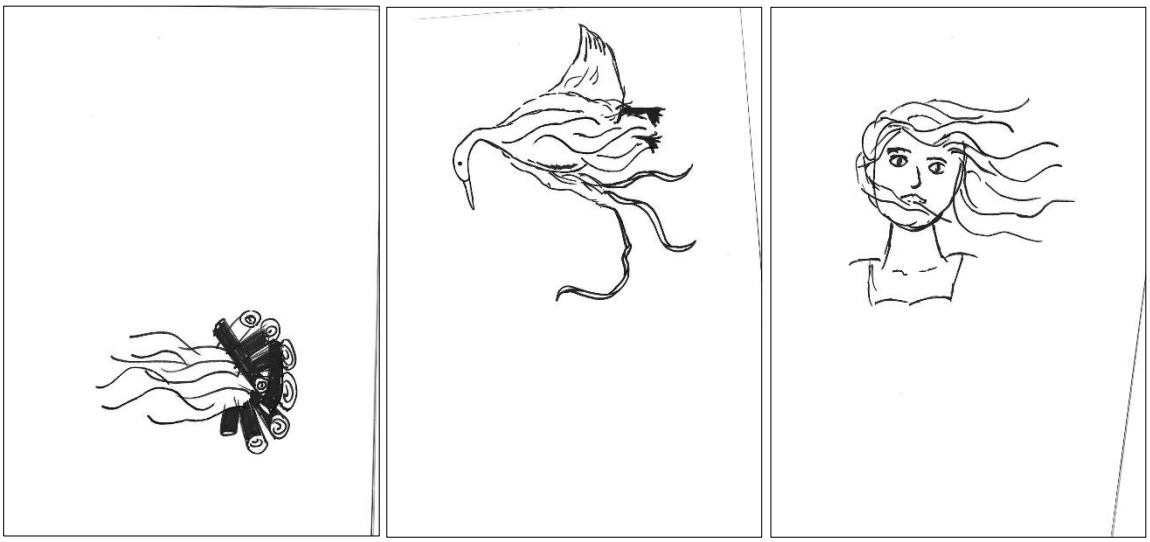
PD (0. 00025) PD (0.11) SC (0.02)

High in Self-similarity (PHOG-based)



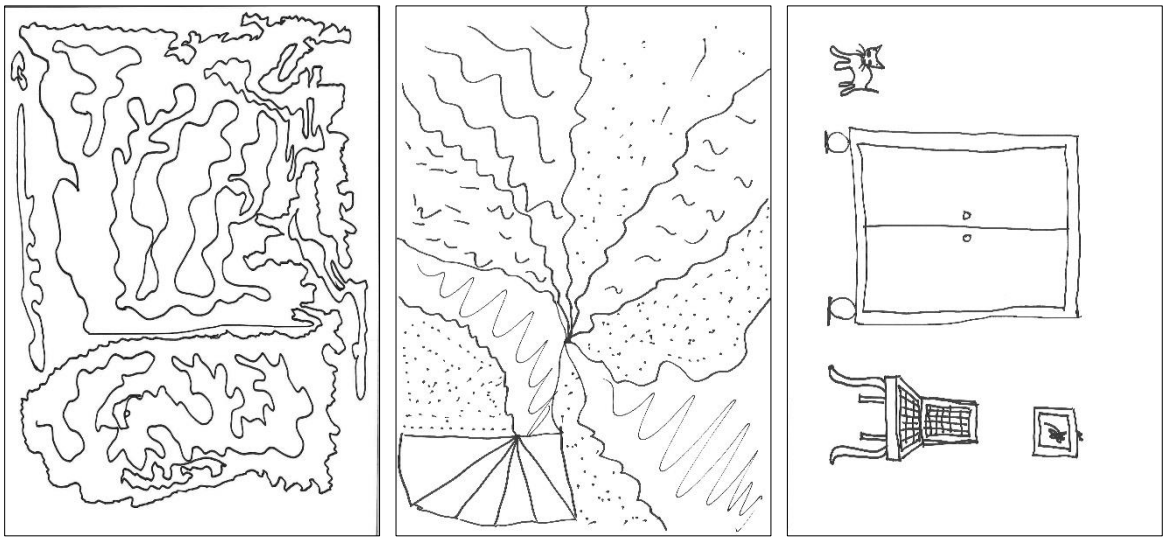
HC (0.77) PD (0.74) HC (0.73)

Low in Self-similarity (CNN-based)



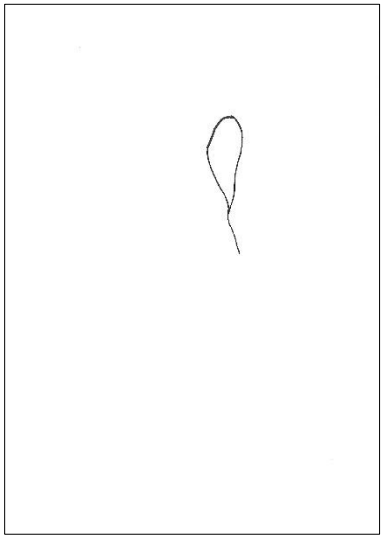
SC (0.08) SC (0.08) SC (0.08)

High in Self-similarity (CNN-based)

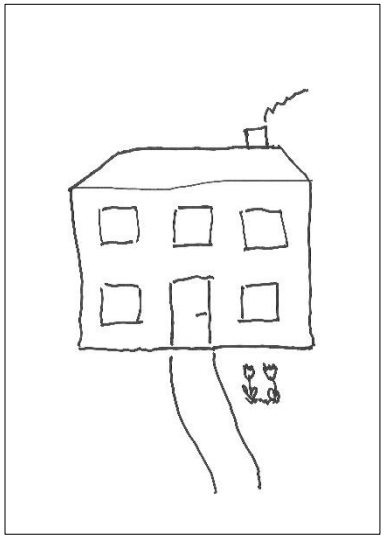


SC (0.90) HC (0.88) HC (0.88)

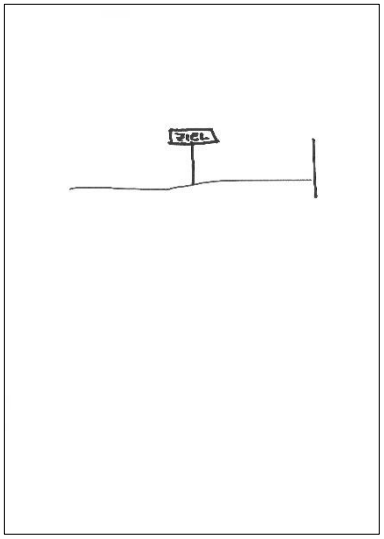
Low in Homogeneity



PD (35.93)

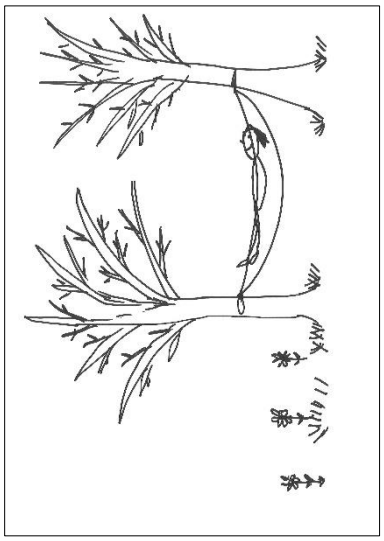


HC (36.79)

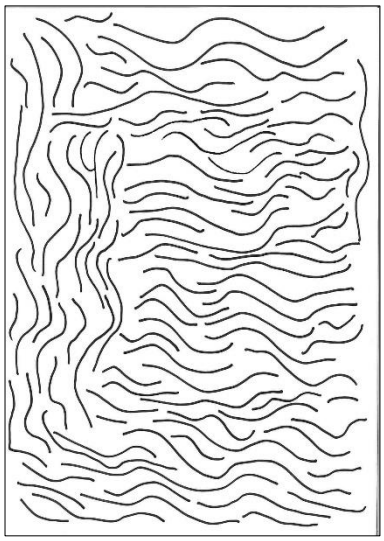


HC (41.22)

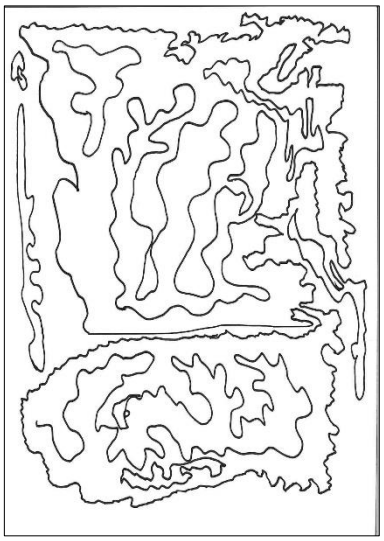
High in Homogeneity



HC (99.70)

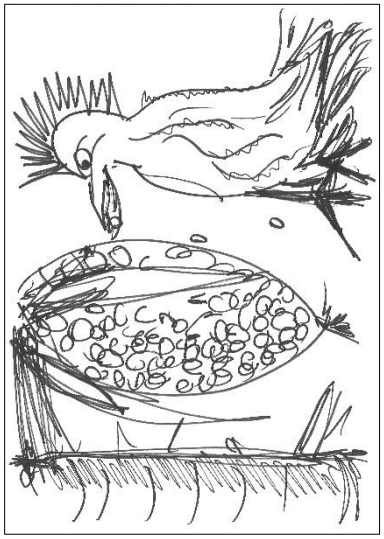


SC (99.41)

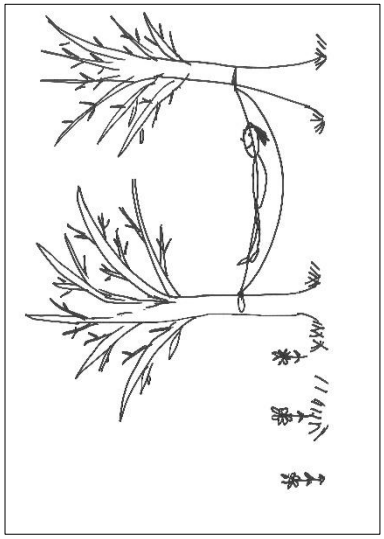


(98.88)

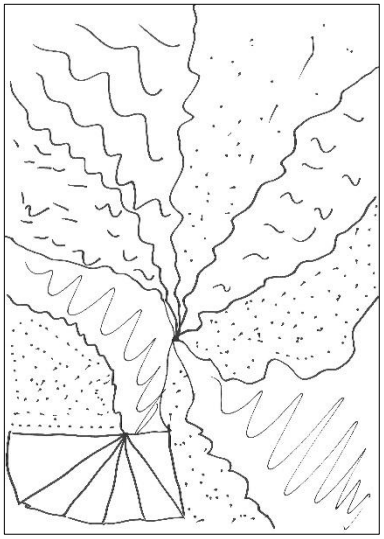
Low in Anisotropy



HC (0.00039)

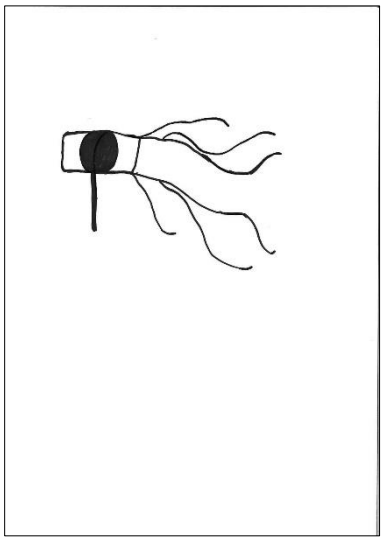


HC (0.00042)

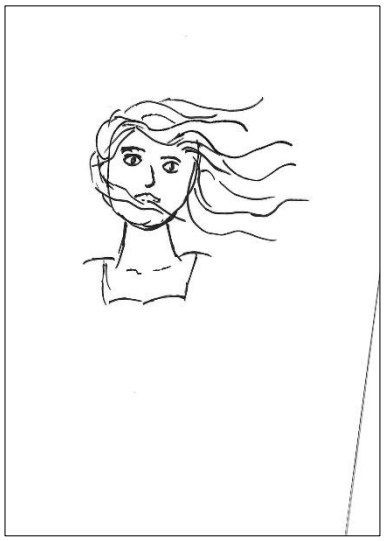


HC (0.00044)

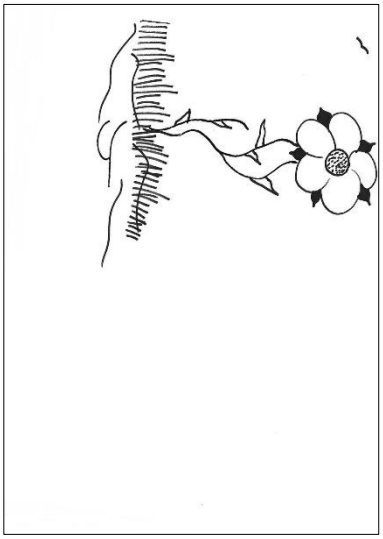
High in Anisotropy



SC (0.00229)

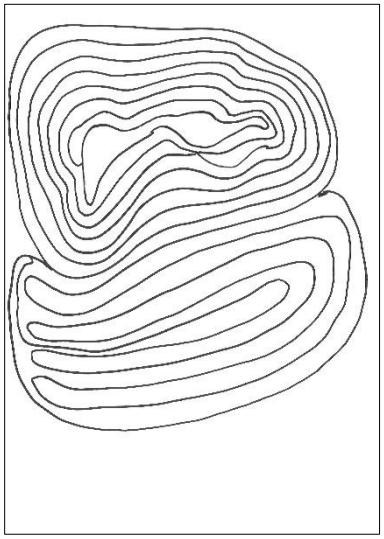


SC (0.00225)

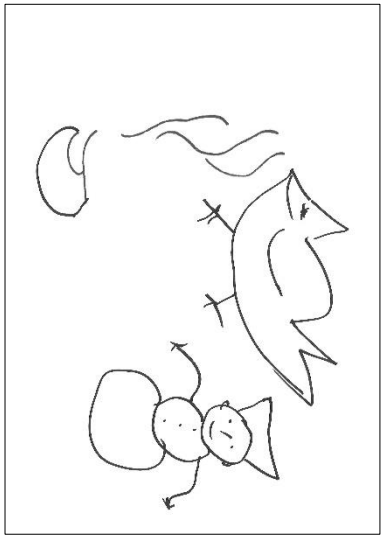


SC (0.00224)

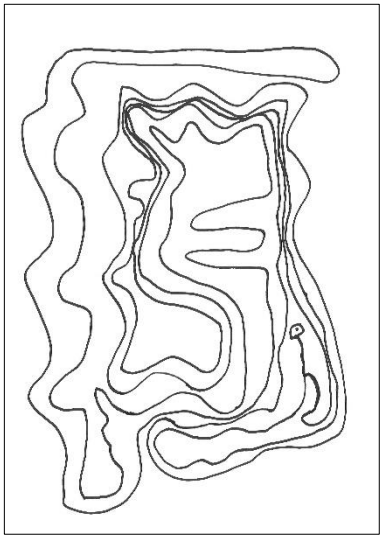
Low in 1st EOE



HC (2.27)



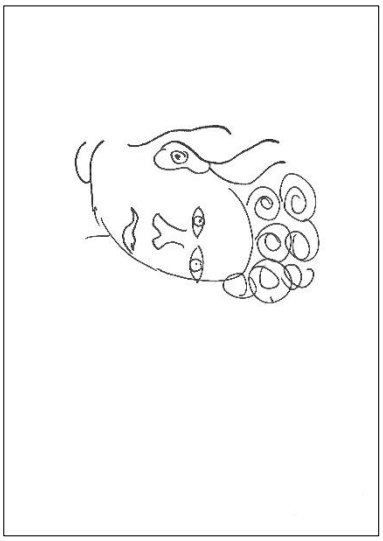
HC (2.35)



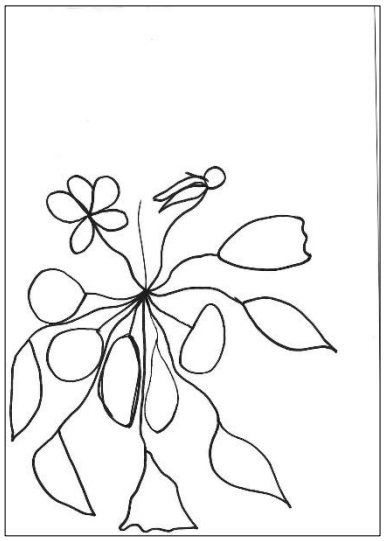
HC (2.38)

High in 1st EOE

HC (4.57)

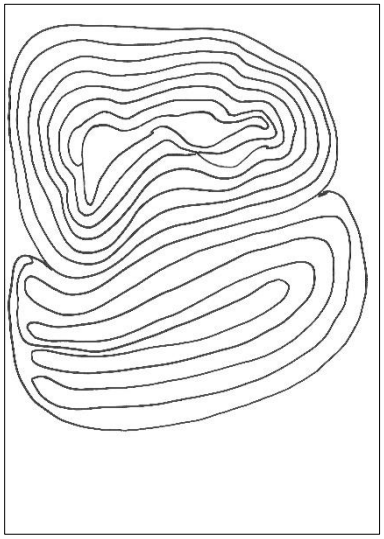


PD (4.57)

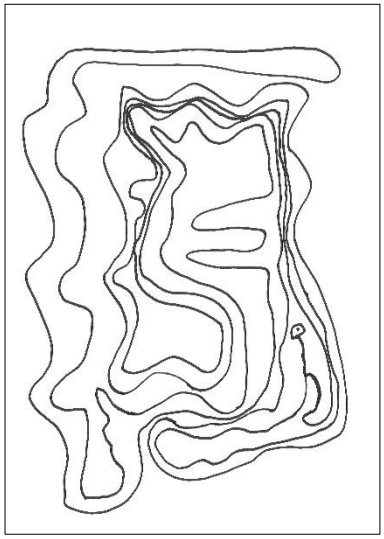


SC (4.57)

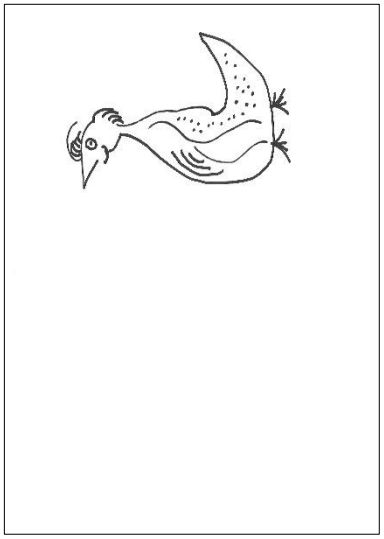
Low in 2nd EOE



HC (2.71)

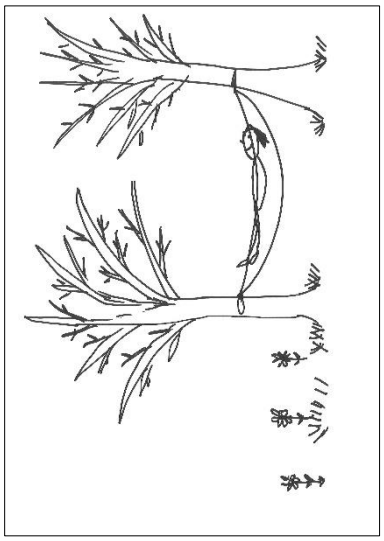


HC (2.85)

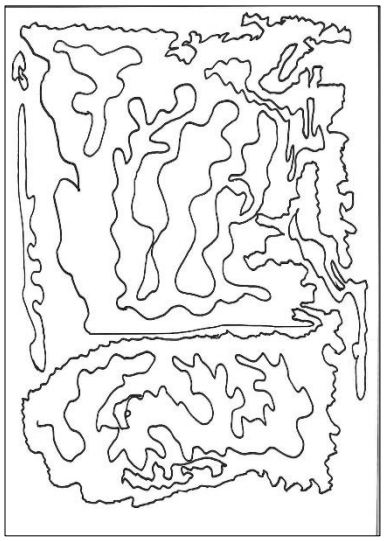


HC (2.99)

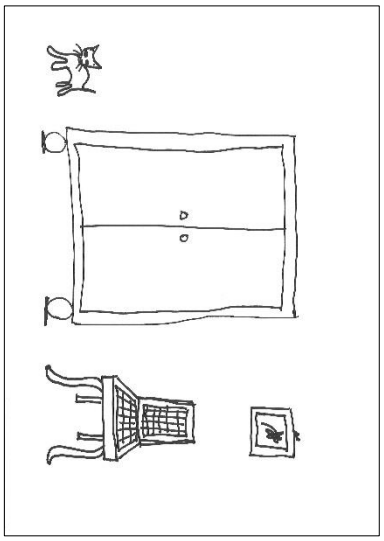
High in 2nd EOE



HC (4.57)

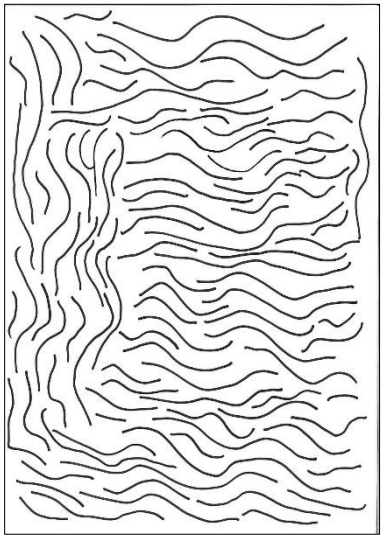


SC (4.57)

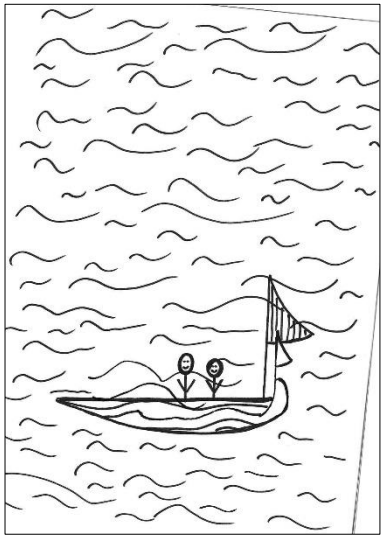


HC (4.56)

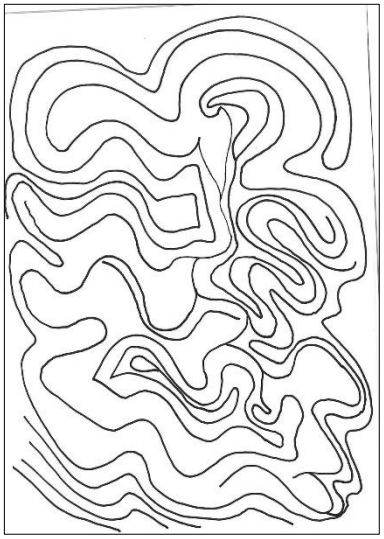
Low in Sparseness



SC (0.00023)

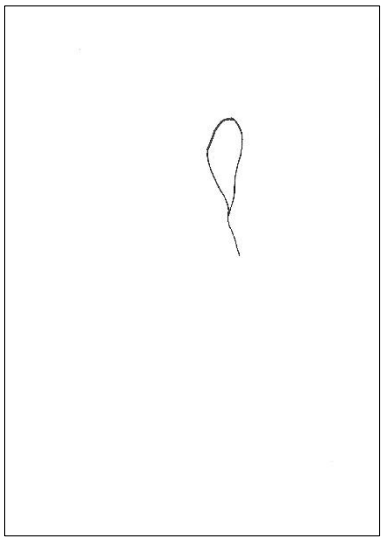


SC (0.00029)

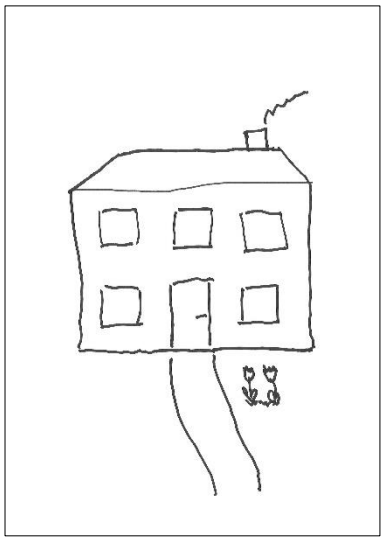


SC (0.00030)

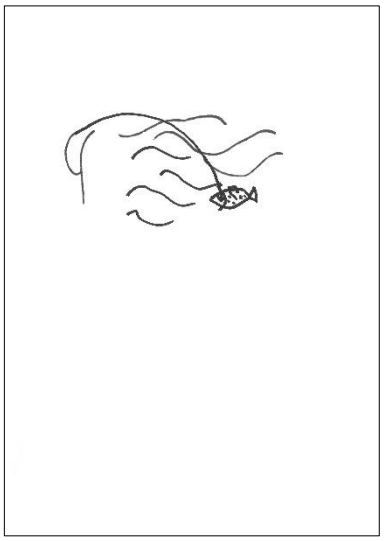
High in Sparseness



PD (0.00166)



HC (0.00164)



HC (0.00163)

Appendix 3.

Rationale for Post Hoc Analyses

Post hoc pairwise comparisons were conducted only for effects involving the within-subject factor Cue when the corresponding omnibus repeated-measures ANOVA indicated a significant main effect of Cue or a significant interaction involving Cue. Pairwise comparisons were Bonferroni-corrected to control for multiple testing. No post hoc tests were conducted for between-subject factors with two levels (Group or Gender), as the omnibus tests already represent the only possible comparisons.

Post hoc pairwise comparisons for significant main effects of Cue

Feature	Comparison	Mean Difference	p (corrected)
Edge density	Cue 1 vs Cue 2	0.133	.002
	Cue 1 vs Cue 3	0.112	.013
Mirror symmetry	Cue 1 vs Cue 2	0.136	.001
	Cue 1 vs Cue 3	0.107	.017
DCM distance	Cue 1 vs Cue 2	−3.598	.043
	Cue 1 vs Cue 3	−4.290	.020
CNN symmetry (left–right)	Cue 1 vs Cue 2	0.082	< .001
	Cue 1 vs Cue 3	0.037	< .001
	Cue 2 vs Cue 3	−0.045	< .001

Feature	Comparison	Mean Difference	p (corrected)
CNN symmetry (up–down)	Cue 1 vs Cue 3	0.038	.001
	Cue 2 vs Cue 3	0.049	< .001
CNN symmetry (combined)	Cue 1 vs Cue 3	0.043	< .001
	Cue 2 vs Cue 3	0.027	.021
Fourier slope	Cue 1 vs Cue 3	0.043	.028
	Cue 2 vs Cue 3	0.051	.009
Fourier sigma	Cue 1 vs Cue 2	0.013	< .001
	Cue 2 vs Cue 3	−0.015	< .001
3D fractal dimension	Cue 1 vs Cue 3	0.022	.011
	Cue 2 vs Cue 3	0.029	.002
Anisotropy	Cue 1 vs Cue 3	6.75e-05	.002
	Cue 2 vs Cue 3	1.04e-04	< .001

Note. Only statistically significant pairwise comparisons are shown. p-values were Bonferroni-corrected.

Post Hoc Comparisons for Interaction Effects

Post hoc comparisons for significant Cue × Group and Cue × Gender interactions

Feature	Interaction	Comparison	Mean Difference	p (corrected)
Fourier sigma	Cue × Group	HC Cue 1 vs PD Cue 1	0.040	< .001
		HC Cue 2 vs PD Cue 2	0.021	< .001
		HC Cue 3 vs PD Cue 3	0.023	.022
1st-order EOE	Cue × Group	HC Cue 1 vs PD Cue 2	0.432	.009
		HC Cue 1 vs HC Cue 2	0.231	.014
	Cue × Gender	Cue 1 (female vs male)	—	.035
2nd-order EOE	Cue × Gender	Cue 2 (female vs male)	—	.042

Note. Only comparisons contributing to significant interactions are reported. Detailed descriptive statistics are available upon request.

Appendix 4.

R Code for Principal Component Analysis

```
# Load required packages

library(psych)


# Read data

data <- read.csv("PCA.csv", header = TRUE)


# Select averaged aesthetic features

features <- data[, c(

  "RMS.contrast_Gesamtergebnis",

  "Lightness.entropy_Gesamtergebnis",

  "Complexity_Gesamtergebnis",

  "Edge.density_Gesamtergebnis",

  "Mirror.symmetry_Gesamtergebnis",

  "Balance_Gesamtergebnis",

  "DCM.distance_Gesamtergebnis",

  "DCM.x.position_Gesamtergebnis",

  "CNN.symmetry.left.right_Gesamtergebnis",

  "CNN.symmetry.up.down_Gesamtergebnis",

  "CNN.symmetry.left.right...up.down_Gesamtergebnis",

  "Fourier.slope_Gesamtergebnis",

  "Fourier.sigma_Gesamtergebnis",

  "X2D.Fractal.dimension_Gesamtergebnis",

  "X3D.Fractal.dimensionGesamtergebnis",

  "Self.similarity..PHOG.Gesamtergebnis",
```

```
  "Self.similarity..CNN._Gesamtergebnis",
  "Homogeneity_Gesamtergebnis",
  "Anisotropy_Gesamtergebnis",
  "X1st.order.EOE_Gesamtergebnis",
  "X2nd.order.EOE_Gesamtergebnis",
  "Sparseness_Gesamtergebnis"
)]

# Remove incomplete cases
features_complete <- features[complete.cases(features), ]

# Assess sampling adequacy
KMO(cor(features_complete))
cortest.bartlett(cor(features_complete), n = nrow(features_complete))

# Principal Component Analysis (unrotated)
pca_res <- prcomp(features_complete, center = TRUE, scale. = TRUE)

# Extract component scores
scores <- as.data.frame(pca_res$x[, 1:4])
scores$Group <- data$Gruppe[complete.cases(features)]

# MANOVA on component scores
manova_res <- manova(cbind(PC1, PC2, PC3, PC4) ~ Group, data = scores)
summary(manova_res, test = "Pillai")
summary.aov(manova_res)
```

Appendix 5. Abstract - English

Parkinson's disease (PD) is associated not only with motor impairments but also with alterations in visuomotor integration and perceptual processing. While prior research has documented handwriting abnormalities and anecdotal changes in artistic behavior, little is known about whether PD systematically alters the structural properties of free drawings. The present study examined whether drawings produced by individuals with PD differ from those of age-matched healthy controls (HC) in objective, image-based features.

62 individuals with idiopathic PD, 69 age-matched controls, and 57 younger student controls completed a cue-based drawing task. Drawings were analyzed using a computational image-analysis framework (Aesthetic Toolbox) that extracted 24 structural features capturing contrast, symmetry, spatial distribution, fractal organization, and frequency-domain properties. Multivariate statistics, principal component analysis (PCA), and gradient-boosted machine-learning classification were applied.

Results revealed significant group differences between PD and HC participants in features related to global symmetry, spatial organization, and multiscale structure, whereas overall complexity remained largely preserved. Machine-learning classification distinguished younger participants from older groups with high accuracy, while PD and HC drawings showed moderate but above-chance separability. Feature-importance analyses indicated that fractal and frequency-based measures contributed most strongly to classification.

These findings demonstrate that PD is associated with subtle but systematic alterations in the structural organization of drawings. Computational image analysis provides a reproducible framework for quantifying visuomotor changes in neurodegenerative conditions beyond subjective evaluation.

Appendix 6. Abstract – Deutsch

Morbus Parkinson (MP) ist nicht nur durch motorische Beeinträchtigungen gekennzeichnet, sondern geht auch mit Veränderungen des visuomotorischen Zusammenspiels und der Wahrnehmungsverarbeitung einher. Während frühere Studien vor allem Handschriftanomalien sowie vereinzelte Veränderungen im künstlerischen Verhalten beschrieben haben, ist bislang kaum untersucht worden, ob MP die strukturellen Eigenschaften freier Zeichnungen systematisch beeinflusst. Ziel der vorliegenden Masterarbeit war es daher zu prüfen, ob sich Zeichnungen von Personen mit MP in objektiven bildbasierten Merkmalen von denen altersgleicher gesunder Kontrollpersonen (HC) unterscheiden.

An der Studie nahmen 62 Personen mit idiopathischem MP, 69 altersgematchte Kontrollpersonen sowie 57 jüngere Studierende als zusätzliche Vergleichsgruppe teil. Alle Teilnehmenden bearbeiteten eine Cue-basierte Zeichenaufgabe. Die entstandenen Zeichnungen wurden mithilfe eines computergestützten Bildanalyse-Frameworks (Aesthetic Toolbox) ausgewertet, das 24 strukturelle Bildmerkmale extrahierte, darunter Kontrast, Symmetrie, räumliche Verteilung, fraktale Organisation und frequenzbasierte Eigenschaften. Zur Analyse wurden multivariate Verfahren, eine Hauptkomponentenanalyse (PCA) sowie eine gradientenverstärkte maschinelle Klassifikation eingesetzt.

Die Ergebnisse zeigten signifikante Unterschiede zwischen MP- und HC-Teilnehmenden in Merkmalen der globalen Symmetrie, räumlichen Organisation und multiskaligen Struktur, während die Gesamtkomplexität weitgehend erhalten blieb. Die maschinelle Klassifikation unterschied jüngere von älteren Teilnehmenden mit hoher Genauigkeit; zwischen MP- und HC-Zeichnungen zeigte sich eine moderate, aber statistisch überzufällige Abgrenzbarkeit. Analysen der Merkmalsbedeutung ergaben, dass insbesondere fraktale und frequenzbasierte Kennwerte zur Gruppenunterscheidung beitrugen.

Diese Ergebnisse weisen darauf hin, dass MP mit subtilen, aber systematischen Veränderungen in der strukturellen Organisation von Zeichnungen verbunden ist. Computergestützte Bildanalysen bieten damit einen objektiven und reproduzierbaren Ansatz zur Erfassung visuomotorischer Veränderungen bei neurodegenerativen Erkrankungen, der über subjektive Beurteilungen hinausgeht.