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A literature review of online handwriting analysis to detect Parkinson's disease at an early stage

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Abstract
Parkinson's disease (PD) affects millions of people worldwide, it dramatically affects the brain areas' structure and functions. Therefore, it causes a progressive decline of cognitive, functional and behavioral abilities. These changes in the brain result in the degradation of motor skills' performances. Handwriting is a daily task combining cognitive, kinesthetic and perceptual-motor abilities. Thus, any change in the brain areas affects directly on the aspects of handwriting. For this purpose, many researchers have studied the possibility of using the handwriting alterations caused by PD as diagnostic signs, in order to develop an autonomic and reliable Diagnosis Aid System which could strongly detect this pathology at an early stage. This intelligent system could help in assessing and controlling the evolution of PD, and consequently, in the improvement of the patients' quality of life. This paper aims at presenting a literature review of the most relevant studies conducted in the area of the on line handwriting analysis, in order to support PD. Starting by the typical followed procedure which consists of handwriting data acquisition, used materiel, proposed tasks, feature extraction, and finally data analysis. Indeed, according to all the investigated studies, dynamic handwriting analysis is a powerful, noninvasive, and low-cost tool to effectively diagnosis PD. In conclusion of the paper, future directions and open issues are highlighted.

Keywords Parkinson's disease assessment · On-line handwriting analysis · Graphic tablet · Dysgraphia · Kinematics · Fine motor control · Survey

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1 Introduction

Parkinson's Disease (PD), first medically determined by James Parkinson in 1817, is the second most widespread degenerative neurological disease after Alzheimer's disease [21], it is a neurological disorder in the central nervous system. In 2015, this disease affected 6.9 million people globally and is expected to affect 14.2 million people by 2040 worldwide [26]. PD is characterized by the chronic and progressive destruction of dopaminergic neurons. PD dramatically affects the brain areas' structure and functions. Therefore, it causes a progressive decline of cognitive, functional and behavioral abilities. These changes in the brain result in the degradation of motor skills' performances [100].

At the moment when the first symptoms appear, it is estimated that 50% to 60% of the nerve cells of the substantia nigra are already destroyed [62]. Thus, when the symptoms appear, the disease has already on average 5 to 10 years of evolution [39]. Accordingly, early PD detection is still challenging.

Unfortunately, there is currently no cure for PD. Nevertheless, developing an early and reliable Diagnosis Aid System could strongly detect this pathology and help in the control of its evolution, consequently, in the improvement of the patients' quality of life.

Handwriting (HW) is a daily task which is a combination of cognitive, kinesthetic and perceptual-motor abilities. Thus, any change in the brain areas affects directly on the aspects of HW, and can be manifested by micrographia, slower movements, or tremors. These important HW's alterations could be considered as a prominent biomarker of PD [24, 46].

For this purpose, identification of accurate biomarkers is the primary goal of research done on the analysis of online HW in order to early detect PD. Indeed, in the last few years there has been a growing interest concerning this subject, several studies were done on the analysis of online handwriting in order to detect neurodegenerative diseases. Studies conducted on PD can be classified into four categories:

1. Investigating the response to medication and their effects on handwriting in order to quantify the efficiency of treatment and monitor disease progression through the analysis of online handwriting [19, 20, 33, 76, 99, 101].
2. Studying the effect of practicing handwriting [114].
3. Examining changes in HW to better understand the brain body functional relationship [16, 33, 58, 73, 77, 87].
4. Developing a Diagnosis Aid System (DAS) to investigate the adoption of online handwriting as a low-cost objective tool for automatic PD detection [3, 6, 27–30, 32].

   This chapter aims at presenting a review of the most related state of the art studies done on the analysis of online handwriting in order to assess and support the early identification of Parkinson's Disease. The most relevant handwriting tasks and computed features are also highlighted.

   All the studies considered in this review, utilize digitizing tablet technology or Biometric Smart Pen for the online handwriting analysis.

2 Methodology

All the papers included in this review were published in PubMed, Scopus and Google Scholar. Indeed, they all focused on the online handwriting analysis using either digital tablets or the Biometric Smart Pen in order to detect PD at an early stage.

Extensive research was applied based on several keywords and combinations. Concerning exclusion criteria, all papers not relevant to this review's scope were excluded after reviewing their titles, abstracts and full texts. Papers included in this review are either original or review articles, they are written in English and focus on the use of dynamic handwriting. In all the selected papers, 107 articles were published in recognized and indexed journals and only 8 conference papers were included. All the included papers were published between 2012 and 2021.

3 Medical diagnosis of Parkinson's disease

Parkinson's disease is a degenerative pathology which is mainly characterized by a progressive destruction of dopaminergic neurons. Its progression can be described as follows [112]. At the start, the loss of cells happen in the substantia nigra due to unknown factors [57]. Then, it damages the dopamine pathway which generates an insufficient dopamine in these areas (See Fig. 1). Unfortunately, before the first symptoms appear and before the medical diagnosis is made, more than half of these neurons have already disappeared.

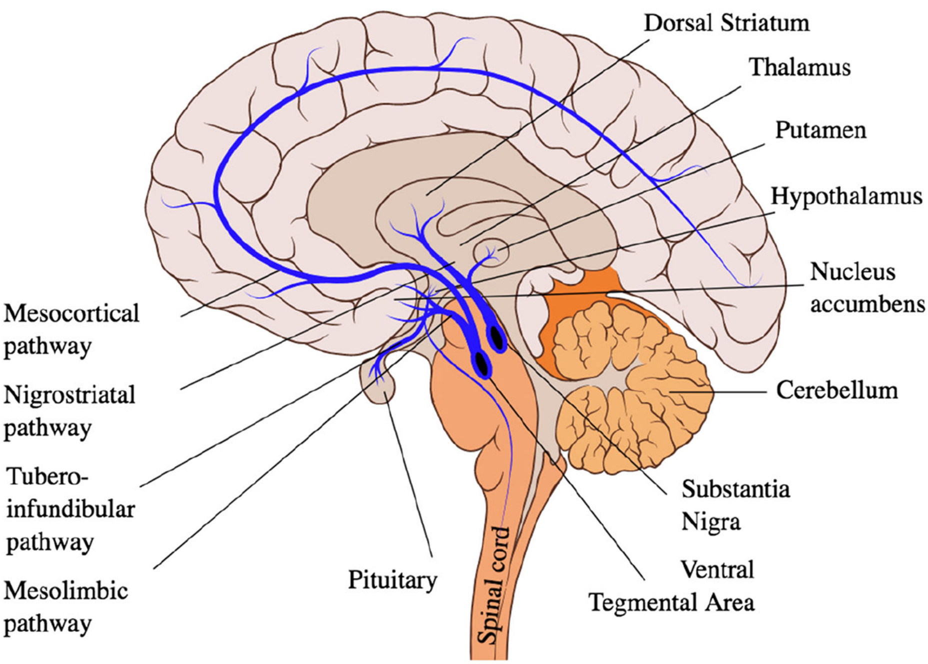

Fig. 1 The progressive cells loss in the substantia nigra area destroying the dopamine pathway

However, some warning signs may exist, such as smell blindness, cramped handwriting, tremor, uncontrollable movements during sleep, voice changes, and stooped posture [91]. The identification of these signs is based on the retrospective declaration of the affected subjects or that of their relatives. The most observed signs are discreet; namely fatigue and concentration difficulties or very often a decrease in performances while performing daily tasks. In the initial stage, the most relevant motor symptoms can include but not by way of limitation to slowness of movement, postural instability, and tremor. Over time, these symptoms can unfortunately make the patient lose its mobility [78]. PD can also cause some mood disorders, such as depression as well as anxiety. Besides, in their early stages, more than a third of PD patients suffer from mood disorders. Finally, the micrographia often appears before the other symptoms, but rarely noticed [112].

In summary, PD symptoms can be classified into three categories:

1. Motor symptoms: Akinesia; Rigidity; Tremor; Postural instability;
2. Non-motor symptoms: Cognitive impairment [34]; Psychiatric disorders [1, 55]; Pain [10]; Dysautonomia; Sleep problems: Restless legs syndrome (RLS) [8] and Rapid eye movement sleep Behavior Disorder (RBD); Color vision: poorer color discrimination and poorer sensitivity to contrasts [74];
3. Prodromal symptoms: Hyposmia [18] (a reduced ability to smell and to detect odors); Constipation [56]; Facial hypomimia [51]; Voice changes [79, 80];

The diagnosis of PD is never obvious and requires expertise. Its purpose is to find out other possible explanations for the symptoms observed and to clarify whether it is PD itself or another pathology namely Parkinson's syndrome [40]. the definite diagnosis of PD requires a post-mortem pathological examination looking for the presence of Lewy body in the brain.

Making a successful clinical diagnosis of PD can be complicated. In fact, there's no test, such as a blood test, that can give a conclusive result. Instead, doctors must carefully analyze symptoms, family history and other factors to draw an accurate conclusion [86].

Several diagnostic criteria exist and the most common is that of the United Kingdom Parkinson's Disease Society Brain Bank (UKPDSBB) [41]. This diagnostic criterion consists of 3 steps. The first serves to establish the presence of a parkinsonian syndrome (defined by the presence of bradykinesia associated with stiffness, tremors at rest, or postural instability). The second step consists in looking for exclusion criteria (which would be in favor of an atypical or secondary parkinsonian syndrome or would reveal a neurological history). The third consists in looking for elements specific to PD (slow and progressive evolution of symptoms, asymmetry, good response to L-DOPA ...). This diagnostic criterion makes it possible to detect PD with 82% success compared to the definite diagnosis made after autopsy [41].

The motor symptoms on which this diagnostic criterion is based only appear after the loss of 50 to 60% of the dopaminergic neurons in the substantia nigra [39] and 60 to 80% of their striatal endings. This implies a rather late diagnosis in the pathophysiological progression of the disease. A major challenge in medical research therefore consists in finding ways to detect the disease earlier, in order to be able to slow down, or even stop, its progression from the start.

Once the diagnosis is made, in order to quantify the progression of the disease and the effects of treatments, several scales are used for PD assessment, which have been methodologically validated. These are clinical scales which are not essential for diagnosis and monitoring, but which can be useful, even necessary during therapeutic evaluations.

These scales are divided into:

- **Global evaluation scale:** Hoehn and Yahr scale [12], allowing the classification of the disease in different stages. It divides the progression of the disease into 5 levels, ranging from the presence of unilateral signs leading to minimal or no functional impairment (stage 1) to confinement to a wheelchair or to bed with loss of autonomy. (stage 5).
- **Analytical assessment scales:** that quantify disability [63].
- **Functional scales:** that measure the consequences of PD on daily activities: Schwab and England scale [94], PDQ-39 (Parkinson Disease Questionnaire) [52] and its abridged version PDQ-8.
- **Multi-dimensional scales:** Unified Parkinson's Disease Rating Scale (UPDRS) which assesses the mental, behavioral and thymic state, the activities of daily life, the motor examination, the treatment's complications. This scale is composed of 4 parts which contain several items, each response being scored from 0 (= normal) to 4 (= severe).
- Part 1 relates non-motor experiences of everyday life. It is completed in part by the investigator from the interview with the patient and in part by the patient, possibly assisted by a caregiver.
- Part 2 deals with motor experiences of everyday life. It consists of a questionnaire self-administered by the patient.
- Part 3 is an engine exam. It consists of a series of motor tests from which the investigator will assess speech, facial expression, rigidity, movements of the fingers, hand, toes, legs, lifting of the body, walking, posture and tremors. For patients already on treatment, this part is usually done in ON (within 3 hours after taking the treatment) and OFF (more than 12 hours since the last medication) to see the effect of the treatment.
- Part 4 aims to assess motor complications. The investigator, based on the examination and his observation, assesses dyskinesias due to treatment and motor fluctuations including dystonia in the OFF state.
- The other scales of assessment mainly concern cognitive functions, mental state, motor fluctuations, dyskinesia, akinesia and tremor [110].

  Indeed, neuroimaging tests can be done as a complete clinical analysis to aid in the diagnosis and monitoring of PD, namely: The brain scanner, Magnetic Resonance Imaging (MRI), Electroencephalography (EEG), Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT).

  Finally, it worth motioning that there exist two types of treatments that reduce the motor symptoms of PD by seeking to overcome the decrease in dopamine in the striatum: dopamine precursors (L-DOPA) and dopamine agonists. For patients for whom medication is not effective enough, surgical treatment is possible: deep brain stimulation. Electrodes are implanted in specific regions of the brain (subthalamic nucleus, or globus pallidus) and deliver weak electric currents there. The mode of action is not yet well understood, but its effect on the various functional neural networks has recently been demonstrated [53], and its efficacy has been proven in patients resistant to usual treatment.

  Medications and surgical treatment reduce the motor symptoms associated with PD but do not slow the progression of the disease. The interest of research on the early diagnosis of PD is to be able, in the near future, to test new treatments (the aim of which would be to stop the progression of the disease) at the prodromal stage of PD, when the brain does not yet have too many irreversible lesions. Indeed, once such a treatment is discovered, it should be given as early as possible to patients with PD in order to stop the progression of the disease.

4 Parkinson's disease: Motor skills and handwriting

In the literature, it has been shown that Parkinson's disease affects motor skills or motor functioning in the preclinical phase and before clinical diagnosis [69, 113]. Handwriting has been used in two main settings to characterize Parkinson's disease: Offline handwriting and online handwriting. Several approaches have already been investigated in the offline domain [69, 113], for instance in [113], the authors have dealt with the problem of PD recognition by using computer vision techniques on an offline dataset consisting of spiral drawings images extracted from the handwriting of 37 PD patients and 18 healthy controls (HCs). Indeed, in [69] N. Zhi et al. have worked on the offline historical signature samples of 12 PD patients.

Currently, several research studies have exploited the quick emergence of digital technologies to analyze writing disorders in patients with these kind of diseases. Most of these studies concerning the online handwriting acquisition are adopted. The major gain of the online handwriting is the ability to acquire and analyze the full dynamic of the handwriting based on the kinematic, mechanical and temporal features [96]. In fact, the dynamic parameters given by the online handwriting acquisition devices are: the position in x and y, time duration, pressure exerted on the surface tablet, pen's azimuth angel w.r.t the horizontal plane, and pen's altitude angel w.r.t the vertical axis [49]. The pen trajectory is recorded when the pen is on surface as well as when it is in air (see Fig. 2) (maximal height is 1.5 cm above the device).

5 Typical followed procedure

Most of the studies conducted on the dynamic analysis of handwriting for the detection of Parkinson's disease generally pursue a common experimental approach: Starting by data acquisition, then feature extraction and at the end data analysis (see Fig. 3). These steps are addressed separately in the coming paragraphs.

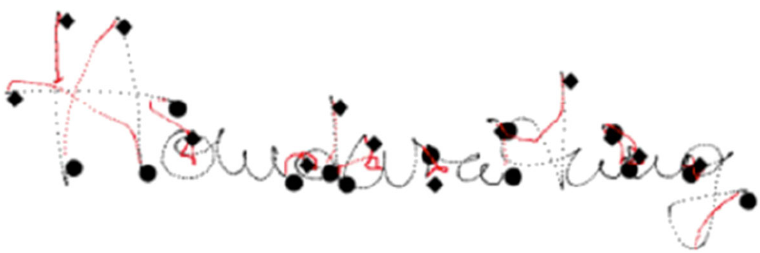

Fig. 2 On surface (Black color) and in air movements (Red color)

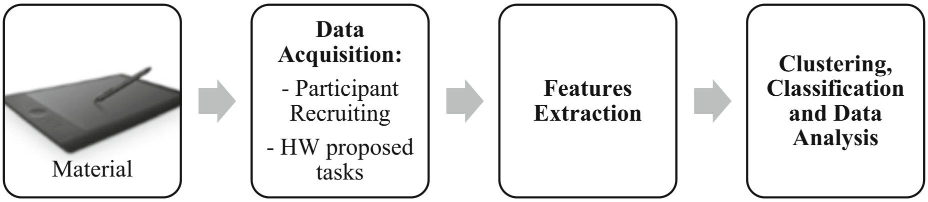

Fig. 3 Flowchart of typical followed procedure of dynamic handwriting analysis

5.1 Data acquisition

At this stage, the most essential steps concern the recruitment of participants, the choice of devices and the definition of the acquisition protocol. The currently available datasets concerning Parkinson's disease are also represented.

5.1.1 Participant recruiting

Regarding the recruitment of participants, several criteria must be taken into account. The most important is to respect the parity of these criteria. The first important parity's point to take into consideration is the cardinality of studied populations. Furthermore, not only the age parity is crucial, since handwriting alteration can be associated to age differences rather than underlying pathological conditions, but also the level of education (typically expressed in years) which can influence directly on handwriting even though the presence of cognitive decline [4]. In some works the handwriting frequency is also considered. The ON or OFF medication is another important aspect taken into consideration for PD patient. For instance, some studies were conducted on PD and dealt with patients under antiparkinsonian treatment [33, 101]. These studies demonstrated that handwriting can significantly changes depending on the level of medical treatment.

Moreover, in order to take into consideration the disease severity, the UPDRS Unified Parkinson's Disease Rating Scale - (part V) score, relating to the Modified Hoehn and Yahr Scale, is a generally used as a rating scale for describing the patient's situation and quantifying the evolution of his symptoms during time [64]. This assessment provides a complete and flexible tool for monitoring the progression of Parkinson's disease and the patient's level of loss of autonomy.

Several studies use also the Mini-Mental State Examination score for the assessment of the cognitive profile of participants [115]. The MMSE is a global cognitive assessment test carried out first for all neurological examinations. It consists of a questionnaire of 30-point comprising questions to assess skills: spatiotemporal orientation, attention and calculation, learning and transcription of information, language and identification, and praxies constructive (the ability to organize a series of movements for a specific purpose by reproducing geometric shapes). It is also crucial to give close and thoughtful attention to participants who have visual problems, whether they have bring their eyeglasses or not so they can execute the handwriting tasks without difficulties. Therefore, any degradation of writing related to this problem and not to neurological problems should be eliminated.

The choice of healthy controls (HCs) group is principally done after passing a cognitive examination by specialists. Generally, elderly and young controls can be also considered;

nevertheless an objective comparison should take into consideration demographic as well as educational characteristics.

5.1.2 Materials

There exists an extensive range of devices for acquiring online handwriting data. The most used devices are graphics tablet [49] and/or Biometric Smart Pens [11] (See Fig. 4). The parameters given by these devices are usually the x- and y-coordinates of the trajectory made by the writer on the surface tablet or in the air, sampled time, angle's pen orientation (azimuth and altitude angle) and pressure exerted by the pen while writing. In some devices, there exists a button status considered as a binary variable assigning 0 for pen-ups (in-air trajectory) and 1 for pen-downs (on-surface trajectory). To make writing conditions familiar and natural to participants, most of studies prefer to fix a sheet of paper on the tablet surface and write with an inking pen [87]. Recently, this field of research have known a new technology called Biometric Smart Pen (BiSP) [70, 102]. These smart pens are electronic multi-sensorics systems which record and analyze handwriting as well as hand and finger movements whether on a paper pad or in air. Position, acceleration, pressure while writing and fingers pressure while holding the pen are captured. It is worth noting that thanks to these technological devices, the analysis of online handwriting is quite simple and non-invasive, it can be done only in the patient's home.

It should be noted that elderly people can be unusual with technological apparatus: Thus, in order to make writing conditions as close as possible to the familiar ones, an effective option is to let them write with an inking pen on a sheet of paper fixed to the digitizer tablet [87]. On the contrary to other diagnostic techniques, namely medical imaging, data acquisition through these apparatus can be done even in the patient's home; furthermore, the handwriting task performance is quite simple and natural, moreover does not need timing or intensive repetitions.

5.1.3 Proposed task

The judicious choice of writing tasks is a fundamental step in the development and implementation of a Diagnostic Aid System based on online handwriting. The choice of proposed tasks is not done randomly, on the contrary, the scientific committees responsible for the careful choice of protocols generally choose tasks ranging from the simplest to the most complex exercises. Some tasks concern writing, and others concern drawing. Some are

Fig. 4 **a**-Digitizing tablet; **b**-Biometric Smart Pen (BiCP)

repetitive tasks and others are reflection tasks. In general, handwriting tasks existing in the literature can be classified into three categories: simple drawing, simple handwriting and complex tasks. More details about these categories are described in the Table 1. It should be noted that, some preliminary tests can be necessary before the execution of the handwriting tasks so that the participant can be familiarized with the equipment.

Simple drawing In the literature, there exist a wide number of simple drawing exercises. The most used ones are the spirals, meanders and circles. These tasks are very simple and easy to perform. These exercises are usually studied for assessing and evaluating tremor by analyzing the handwritten dimension, trajectory, and velocity [22, 33, 70, 73, 88, 89].

Simple Writing In general simple writing tasks consist of either a letter combination or words. So, these tasks contain one or more cursive, continuous and repetitive letters, for instance "*lll*" or "*lele*" [13, 92, 93, 98, 102]. These easy exercises are often used in the literature given their simplicity and their ability to minimizes the language comprehension skills and efforts. According to R.Plamondon [75], the letters "*e*" and "*l*" consist of ascendant and descendent traits defined by their velocity strokes. According to the Delta-Lognormal Kinematic Theory [75] of the handwriting process which "*describes a stroke velocity profile as the output of a system made up of two neuromuscular systems, one agonist (acting in the direction of the movement) and the other antagonist (acting in the opposite direction)*", the "*e*" and the "*l*" letters are composed of two velocity strokes. Furthermore, the use of "*e*" as well as "*l*" means the handwriting of the same character scaled in amplitude. Besides, short words and sentences have been also extensively used (See Table 1). Commonly, words and sentences adopted in these exercises are chosen based on their simplicity in handwriting as well as their easy syntax. Some studies adopted sentences containing a common "core", for instance "*The leveler leveled all levels*" [103]. This approach is adopted to find out how a frequent pattern changes with or without a suffix or a prefix. In some works, they have considered also the letter "*g*", by including words and sentences with up and down traits [32]. In fact, writing a sentence composed of several different words requires an immense degree of movement planification and simultaneous processing of neuro-motor programming load than a simple sequence of identical pattern. A handwritten sentence allows to better assess the motor-planning ability

Table 1 Tasks type

Tasks	Type	Reference
Simple Drawing	Spiral drawing	[22, 42, 88]
	Meanders drawing	[81, 88]
	Circles	[22, 42]
	Horizontal straight lines	[22]
Simple Writing	Repetitive cursive letters	[13, 19, 68, 93, 105]
	Simple words	[27, 29–32, 106]
	Writing own name	[17, 27, 29–32]
	Simple sentences	[87]
	Handwritten signature	[27, 29–32, 77, 101, 111]
Complex Tasks	Adapt the drawing size to a displayed input	[72]
	Time constraints and stroke dimension	[105, 106]
	Drawing Loops while counting	[16]
	Filling an example of bank checks	[87]
	Copying a text composed of several lines	[3, 5–7, 43]

between letters. Actually, a pause or an hesitation between letters or words could indicate the necessity to re-plan the handwriting activity, whereas a fluid handwriting manner can point out the existence of an anticipated motor planning. Indeed, a sentence offers the capturing of a large number of in-air movements between characters and words [32], contrariwise a word can be written without lifting the pen tip from the digitizer tablet.

Complex Writing These handwriting tasks involve several functions namely cognitive, motor and functional ones. In fact, Van Gemmert et al. [103] show that the handwriting of PD patients is more deteriorated when it comes to a secondary task realization in comparison with elderly or young controls. In [8], authors combined handwriting, hearing and counting at the same time. In the handwriting analysis, some studies working more on Alzheimer's Disease (AD) than PD, as AD is mainly characterized by cognitive deficiency, adopting functional handwriting tasks. For instance copying the details of a bank check into convenient fields. In this case, the patient should be capable to read from the source place, locate the objective position and finally write the imposed content there. Some literature works used the Clock Drawing Test (CDT) [14]. CDT allows to detect visual-spatial deterioration. This task as well as many other complex exercises, implicate several neuro-psychological capacities: auditory perception and memory, abstraction ability, visual perception and memory, visual-space functions, programming and execution abilities. Moreover, in [105, 106], authors studied the restraint on time duration as well as the stroke dimension, in addition to the adoption of the visual feedback in order to reach specific targets while writing [36, 97]. In [68], the verbal feedback by reminding patients to write in a bigger manner, has also been considered.

Table 2 Available Datasets (PD = Parkinson's Disease, HCs = Healthy Controls)

Dataset	Groups	Material	Tasks	Country	Reference
PaHaW	37PD – 38 HCs	Wacom Intuos 4 M	Spiral drawing, repetition of characters.	Czech Republic	[32]
NewHandPD	31PD – 35 HCs	Biometric Smart Pen	Spiral and meander drawing.	Brazil	[70]
ParkinsonHW	62PD – 15 HCs	Wacom Cintiq 12WX	Spiral drawing and stability test.	Italy	[47]
EMOTHAW	129 HCs	Wacom Intuos 4	Copying of: pentagons, house drawing; writing four words; loop drawing; Clock Drawing Test; writing of a sentence	Italy	[59]
HandPDMultiMC	21PD – 21 HCs	Wacom Intuos 5	Drawing: repetitive cursive letter ℓ, a triangular wave, a rectangular wave. Repetitive writing of word 'Monday' within the word sequence Monday–Tuesday. Repetitive writing of first and last name.	Lebanon	[95]

5.1.4 Used dataset

Unfortunately, there is a very reduced number of available datasets to explore. In Table 2 we represent a detailed description of each dataset.

The “PaHaW” dataset which is an abbreviation of “The Parkinson’s Disease Handwriting” database, is constituted of several handwriting samples of 37 PD patients and 38 age and gender matched HCs. Participants whose native language is Czech, were asked to perform eight HW exercises following a specific template:

- Drawing an Archimedean spiral;
- Writing in a cursive manner the characters “*l*”, “*le*”, and “*les*”;
- Writing in a cursive way the words: “lektorka” (“female teacher” in Czech), “porovnat” (“to compare” in Czech), and “nepopadnout” (“to not catch” in Czech);
- And finally writing in a cursive manner the sentence “Tramvaj dnes už nepojede” (“The tram won’t go today” in Czech).

The principal characteristics of the selected tasks is their simplicity in writing as well as their manner to be written without lifting the ink pen above the white paper overlaid on the digitizer tablet.

Besides, there exist an original dataset called “HandPD” that contains static (offline) handwriting tasks of PD patients and HCs. Nonetheless, this dataset was extended for the online analysis under the name of “NewHandPD” using the BiSP smart pen. It encompasses handwriting data from 66 participants (31 PD patients and 35 HCs). In this new dataset, participants were requested to draw 10 tasks containing: 4 drawings of spirals, 4 drawing of meanders, 2 circled movements (one circle in the air and another on the paper). Furthermore, the drawn spirals are scanned and studied as images.

The ParkinsonHW dataset contains the handwriting data of 15 HCs and 62 PD patients. It encompasses three categories of handwriting: Static Spiral Test (SST), Dynamic Spiral Test (DST), and Stability Test on Certain Point (STCP). The drawn spirals by participants are all scanned and provided as images. First, concerning the SST test, the participant was invited to retrace three Archimedes spirals which appeared on the digitizer tablet. However, regarding the DST test, the participant was forced to memorize the pattern of the Archimedes spiral and to continue drawing it, since the sample of the Archimedes spiral appear and disappear after a time stamps. As to the STCP task, in order to quantify the patient’s hand stability or tremor, a red point appears in the screen of the graphic tablet, and participants were required to hold the pen on the point without touching the surface. At the date of writing of this thesis, Castrillón et al. [61] are developing a wide set of Parkinsonian handwritten patterns, containing samples from elderly and young HCs.

A multimodal dataset called Parkinson’s disease Multi-Modal Collection (PDMultiMC) was collected including three modalities: online handwriting, speech and eye movements [95]. The dataset of online handwriting is called HandPDMultiMC and it includes online handwriting of 21 PD patients and 21 HCs. The proposed drawing exercises were a triangular wave and a rectangular wave. As for handwriting exercises, they included repetitive cursive letter ℓ, repetitive writing of word ‘Monday’ within the word sequence Monday–Tuesday and repetitive writing of first and last name.

Recently, the EMOTHAW (EMOtion recognition from HAndWriting and draWing) was developed to examine emotional states. This dataset does not include PD patients, but the used exercises are typically adopted in studies dedicated to PD [59], however, this database could be useful for comparison aims. Unfortunately, most research has been conducted on reduced sets of PD patients and HCs.

5.2 Feature extraction and methods

The raw handwriting data acquired by the digitizer apparatus are generally enhanced using the well-known signal pre-processing techniques: Starting by filtering, reducing noise and smoothing the signal. These standard algorithms can be applied, nevertheless their adoption could lead to the loss of crucial information. For instance, the normalization of the signal duration can be done in order to obtain all S(n) sequences of the same length, this technique is often adopted in the verification of signatures [45]. Nonetheless, in the handwriting analysis for the early detection of neurodegenerative diseases, it could result to the loss of important information. Sometimes this information can be a discriminative feature, and can associated to the time spent in performing the handwriting task by the participant. Based on this interpretation, it is familiar to skip the pre-processing steps [109].

The horizontal and vertical coordinates of the handwritten trajectory are recorded by the digital apparatus. Those components of handwriting are divided into two categories of sequences: On-surface and in-air movements, according to their pressure values and sometime to their button status.

In the literature, a stroke is defined as a single continuous and linked trait of the handwritten trajectory, which means the on surface pattern made between two successive pen-lifts. Based on these parameters given by the digitizer device, various features could be computed:

- Kinematic features: Horizontal, vertical and tangential velocity, acceleration, and jerk, number of changes in velocity (NCV), and number of changes in acceleration (NCA). NCV and NCA are computed respectively as the number local extrema of tangential velocity and acceleration. These features are computed for on-surface and in-air movements. Displacement parameter stands for the trajectory made between two consecutive points during handwriting. It gives an accurate approximation of the handwritten pattern. Indeed, based on this displacement parameter, the velocity, acceleration and jerk features can be derived respectively as the first, second, and third derivatives of displacement. Similarly, these features are computed for both horizontal and vertical directions.
- Mechanical features: Typically based on the pressure parameter, several features can be computed, namely: Mean pressure, number of changes in pressure vector (NCP) which means the number of local extrema of tangential pressure, and relative NCP [32].
- Spatiotemporal features: Encompass stroke duration, size, speed, height and width. In addition to on-surface and in-air time, and their normalization and ratio. Total time spent in the handwriting of the entire task is also calculated.
- Entropy and energy features: These type of features are recently used in the literature, and computed for on-surface and in-air strokes. They allow to capture the fine movements irregularities and deteriorations [30]. This category of features include: Shannon and Rényi entropy [37]; signal-to-noise ratio (SNR) [23]; and Empirical Mode Decomposition (EMD) [35]. Empirical Mode Decomposition divides in an iterative manner the handwritten signal into nominal Intrinsic Mode Functions (IMFs) [9], which are functions that respond to two conditions: (1) the computed number of extrema and the number of zero

crossings are either equal or differ by maximum one, and (2) the average of their upper and lower envelopes is equal to zero.

Generally, in order to accurately interpret the obtained values and results, for each feature vector, statistical functions are computed. Namely mean, standard deviation, kurtosis, skewness, median, mode, moments, percentiles, etc. It is worth mentioning that before the classification step, the feature vectors are normalized accordingly to have zero as mean and one as variance.

- Model-based features: In [2] authors used a different approach to study the handwriting changes, based on the Kinematic Theory of Rapid Human Movements [9, 35], namely sigma-lognormal $\sum\wedge$ model. This model is highly recommended, given its reliable results in several studies, such as the verification of online signature [104], and the detection of graphomotor abilities in children [15]. The major benefit of this novel approach is that it relies on a physiological model of the production of human movement which results a better characterization of the invisible handwriting specificities of writers.
- Automatically learned features: Based on deep learning models, some recent studies [2] used the convolutional neural networks in order to automatically extract features from static images retrieved through information of online handwriting.

In Table 3 represents a detailed description of the most used features in the literature. In conclusion, all categories of features have led to successful results, both directly measured through devices or derived from them. In fact, the categories of kinematic and spatiotemporal features are capable to detect if the handwriting is fluent or there exist some abnormalities in it. Features automatically extracted through deep learnings techniques provide, in general, relevant and non-redundant information. In a very recent study [3], for the first time, authors have used the pen inclination features, reporting promising results.

5.3 Data classification and analysis

This section is partitioned into two categories of studies: First we discuss studies based on statistical analysis, and second focus on classification studies. Generally, this is the last step, and its goal is to discover effective patterns able to support decision making.

In Table 4 we represent the major results of the statistical studies conducted on PD patients' handwriting. Overall, we can conclude that PD patients suffer from irregularities in motor activities. It is clear in their reduction in amplitude and dimension of strokes in so called-on micrographia. They also undergo slowness of movements, tremor, bradykinesia, rigidity and akinesia. It is worth noting that tasks described in Table 4 are classified in an increasing order according to their complexity. However, in recent times, all the studies concentrate on the development of reliable computer aid systems able to detect Parkinson's disease at an early stage, based on algorithms of machine learning and statistical pattern recognition techniques.

5.3.1 Approaches using statistical tests

Based on statistical analysis, most of the literature studies focused on the investigation of the handwriting changes due to aging. For instance, the ANOVA analysis of variance is

Table 3 Most generally adopted features, similarly computed for both on-surface and in-air movements

Features	Description	Observation
Device parameters		
Position	(X,Y) coordinates of the handwritten pattern.	They are adopted to derive the geometrical trajectory of HW.
Time Stamp	Sampled time information of handwritten pattern.	It is adopted to compute the temporal duration of the handwriting task.
Pen Pressure	Pressure exerted on the surface device.	Pressure reveals irregular values in PD patients due to cognitive and motor abnormalities.
Azimuth angle	Angle between the pen and the surface plane.	They are used for the first time in [3], and appear to discriminate between PD patients and HCs.
Altitude angle	Angle between the pen and the plane vertical to the surface.	
Button status	Indicates whether the pen is on-surface or in-air.	Separating between on-surface and in-air strokes, it shows how the two HW modalities carry on nonredundant information.
Kinematic		
Displacement	Trajectory while writing.	Commonly used to derive other kinematic features.
Velocity	Change rate of displacement w.r.t. time.	PD patients do not write with the same fluency as HCs. In fact, they have lower HW velocity, with repeated acceleration peaks, and higher wrist jerk values.
Acceleration	Change rate of velocity w.r.t. time.	
Jerk	Change rate of acceleration w.r.t. time.	
NCV/NCA	Number of local extrema of velocity and acceleration respectively.	Allow to detect the fluidity of the HW movement. Fine automated movements are characterized by smooth velocity and acceleration profiles.
Spatio-temporal		
Stroke length	The size of strokes' path .	Patients suffering from PD can have micrographia.
Stroke height/width	Strokes' height and width.	
Stroke duration	Duration of movement per stroke.	The mean time duration of a PD patient is generally longer than in that of a HCs.
Time	Time duration spent on-surface and in-air while writing.	
Features	Description	Observation
Entropy and energy		
Entropy	Features computed through the Entropy.	These measures allow to capture the randomness and abnormalities of fine motor control.
SNR	Features computed through the signal-to-noise ratio.	
EMD	Features computed through the empirical mode decomposition.	
Model-based		
sigma−lognormal $\sum\wedge$-based	Features of the $\sum\wedge$ reconstruction of the handwritten trajectory.	Investigating the dynamics of handwriting while producing the writing activity.
Automatically extracted		
Deep-learning models	Features automatically extracted by deep learning techniques trained on static images of the dynamic information of handwriting.	Provide relevant and non-redundant information.

commonly used to quantify the group differences through the use of different computed features of handwriting.

The first row in Table 4 concerns studies conducted on simple drawing exercises or simple writing of sentences. The main finding of the studies is that patients suffering from PD have slower movement than HCs. For instance, in [87] participants were invited to perform handwriting on a paper fixed on the tablet, by writing their names and copying an imposed address. Statistical measures were computed for each task namely mean pressure and speed, the spatial and temporal features were also computed for each handwriting stroke. The obtained findings showed that those two exercises are efficient to differentiate between online handwriting of PD patients and that of HCs. In fact, PD patients are characterized by a reduced length, width and height of strokes, and slower speed. Similarly, the same results were obtained for the studies of the second row. For example, in [58] authors analyzed various works conducted on handwriting of PD patients. These studies were conducted on digitizer tablets or simply with ordinary pencil- and-paper measures, besides their results show that kinematic and spatio-temporal features are discriminant between PD patients and HCs. Indeed, Letanneux et al. [58] specially found that kinematic features namely velocity discriminates not only between handwriting of PD patients and that of HCs, but also between PD patients on and off medication. However, they found that features computed on dimension of handwritten strokes are not very effective in the differentiation between the two cognitive profiles. Furthermore, authors propose the term "PD dysgraphia" which signify that deteriorations due to Parkinson's disease can alter the handwriting kinematics and fluency without necessarily altering handwriting dimension. Thus, it is clear to say that dynamic and kinematic

Table 4 Representation of statistical studies conducted on handwriting of PD patients

References	Tasks	Results
[15, 17, 73, 77, 87, 97, 104];	Drawing meanders, circles, and spirals. Writing Sentences and names. Copying task.	Slower movements.
[16, 33, 58, 73, 77, 87];	Drawing loops. Writing Sentences and names. Copying task.	Reduced size.
[15, 54, 73, 93, 103];	Drawing meanders, horizontal, straight forward and backward slanted lines, circles. Writing sentence.	High tremor and jerk in PD patients.
[36, 68];	Drawing figure and writing "llll".	Visual feedback is important to PD patients in order to increase their stroke size.
[36, 104];	Drawing figure. Drawing while adjusting the size based on visual information. Writing" llll" beneath different dimension and time conditions.	PD patient are barely able than HCs to adjust the dimension of their writing.
[19, 20, 66, 76, 99, 101];	Drawing circles before and after treatment. Writing "llll", "eeee" and sentence before and after the treatment. Writing the same sentence, consisting of 5 words with 24 characters several times.	Treatment reduces main PD handwriting degradations.
[108, 114];	Writing under visual and auditory feedback.	Training on writing a specific task can help PD patients to increase their handwriting size, writing speed and motor function of hands.

features are appropriate for the diagnosis and monitoring of PD, and also for investigating the effectiveness of a given medication.

In the third row of Table 4, we represent studies that found high tremor and jerk in handwriting of PD patients while drawing circles and lines in various orientations. As for [93], the authors invited participants to draw circles, spirals, lines, repeated letters “elelelel” and finally to write a sentence. Authors were particularly interested in recording pen tip pattern while performing the handwriting tasks. The findings reveal that these type of exercises provide unbiased measures for tremor and micrographia of PD patients.

In addition, the visual feedback of handwriting is very helpful for PD patients to increase their stroke dimension as reported by Oliveira et al. [68] and Fucetola and Smith [36]. These studies which are the subject of the fourth line in Table 4, asked their participants to draw a figure or to write “llll”. Although, it is worth noting that PD patients still are less capable to adjust the dimension of their writing in comparison with HCs as described by Van Gemmert et al. [104] and Fucetola and Smith [36] (See the fifth row of Table 4).

Concerning studies classified in the sixth row of Table 4, they involve tasks conducted on PD patients before and after treatment. The participants were invited to draw circles and write “lll” and “eeee”. The main findings show that, thanks to medication, the handwriting alterations of PD patients are reduced and stabilized.

Finally, in the last row of Table 4, Ziliotto et al. show that training on writing with visual and auditory feedback helps PD patients to stabilize and increase their handwriting dimension. Indeed, in [108] authors revealed that 4-week handwriting exercise with a specific handwriting practice book appeared to improve writing speed and fine motor function of hands.

5.3.2 Approaches using classification

In recent times, all the studies concentrate on the development of reliable computer aid systems able to detect Parkinson’s disease at an early stage, based on algorithms of machine learning and statistical pattern recognition techniques [85]. A noticeable contribution to the use of machine learning algorithms to the automatic discrimination between PD patients and HCs was done by Drotár et al. Indeed, Drotár et al. propose a new PD on line handwriting dataset, containing handwriting data of both PD patients and HCs. Authors conducted several studies and experiments on their own dataset. This dataset contains drawing and writing tasks namely Archimedean spiral, repetitively writing simple syllables and words, and writing of a sentence. In fact, all their research works were conducted on this same dataset, i.e., PaHaW, which they made freely available. For example, in [32], in order to detect differences between PD patients and HCs, researchers used three classifiers: k-Nearest Neighbours (K-NN), AdaBoost and support vector machines (SVM), and found that SVM was the best performing one. Authors adopted new features based on the pressure applied over the writing surface. The principal features computed through pressure vector, were the mean value of pressure exerted on the surface tablet while writing and the rate of pressure changes w.r.t time. Based on the correlation coefficients, authors study the relationship between pressure and kinematic computed features.

Similarly, in another study, Drotár et al. propose in [30] new features in addition to the standard kinematic handwriting features. These new proposed features encompass entropy, signal energy, and empirical mode decomposition of the handwritten signals. In fact, it is shown that these novel measures can help at understanding the data. These features were computed only for on-surface strokes. The authors used supervised learning classifiers namely support vector machines (SVM) [30] and trained it on all computed features. They found that SVM gave the best accuracy values in comparison with other standard approaches. These same authors, propose in [97] to compare the prediction potential of classifiers models trained on each task individually, then they trained the same classifiers by combining all tasks together. The findings show that the best accuracy was achieved by the fusion of all tasks. However, in [28] Drotár et al. sought to know to what extent classification performance can be ameliorated by taking into account on-surface movements and in the air movements, knowing that the two modalities seem to relate to non-redundant information. Accordingly, they found that in-air movements hide precious information than on-surface movements. These results were also confirmed in [29] by using several feature selection techniques.

It is worth noting that, the spiral task adopted by Drotár et al. did not achieve significant accuracy classification rate. This problem could be due to the adoption of measures dedicated only for handwriting. Alternately, using deep learning algorithms [83, 99] could help to overcome this problem by providing new features.

In a study proposed by Rosenblum et al. [87], participants were invited to write their name and copy an imposed address in a specific target. Based on the standard computed features of handwriting, they found that compared to HCs, PD patients have a reduced size stoke, exert less pressure, and need more time duration. Indeed, these computed features can help to accurately detect PD patients and HCs. Besides, Rosenblum et al. were interested to study the importance of in air movements merged with on-surface movements, given that these two modalities contain non-redundant information. As reported by the authors, in-air time express the action of planning the next movement, which can clearly give a sight of the cognitive capacities of the writer.

Some studies however used the technology of the electronic biosensor BiSP smart pen, such as ÜnlÜ et al. [24]. Relying on the pressure information given by BiSP pen and the recorded tremor, authors obtained an 0.933 of area under the ROC curve. Authors showed that the patient's tremor is less noticeable while writing on the tablet's surface, that is to say that PD patients stabilize their tremor while they are in movement, however the resting tremor occurs more when the muscle is relaxed.

Another study in [70], used also the electronic biosensor BiSP smart pen. Pereira et al. proposed a dataset called "NewHandPD", consisting of handwriting data collected using the BiSP. This dataset compasses drawings of spirals and meanders. Each sensor of the used device provides the entire signal captured while performing the handwriting tasks sampled point by point; thus, it can be described subsequently as a time series. Pereira et al. adopted Convolutional Neural Network CNNs and meta-heuristic-based optimization algorithms to tune up the optimized network hyper-parameters considering their high capacity to learn without human intervention. Therefore, the major contribution of this study is the application of a deep learning-oriented approach to facilitate the diagnosis of PD as well as the design of a signal-based dataset. Similarly, in references [2, 71], authors have extended the main finding of the previous study. In [71] CNNs were adopted to extract and learn features precisely from time-series-based images. Authors supposed that the texture-oriented features are capable to detect the tremors all along handwriting. Besides, in reference [2], authors used the recurrence plot technique in order to map the signals provided by the pen into static image domain. Then, these images are exploited to assign a CNN how to extract and lean relevant features.

In fact, a repetitive plot allows to visualize recurrent events of high dimensions by their projection on low-dimensional representations. Authors in [88] conducted a study on drawing Archimedes spiral in order to early detect and diagnose PD. San Luciano et al. found that in general, spatio-temporal features are significantly discriminant between PD patients and HCs. Unlike Drotár et al., San Luciano et al. showed that spiral task seem to be a pertinent quantitative biomarker for the early detection and diagnose of PD.

In [54], Kotsavasiloglou et al. invited their participants to draw a straight horizontal line on the digitizer tablet surface, while managing the pen's velocity as regular as possible. In fact, the authors proposed a new measure by normalizing the velocity variability. This new metric allow to quantify the variability of the pen speed while writing. Authors obtained a good classification accuracy using Bayesian classifier. It is worth mentioning that even if it is a simple drawing task, it gave the possibility to accurately detect differences between the two studied cognitive profiles, because the deficiency manifests itself independently of the complexity of the task. All of the previous studies considered the PD patients group as a single cluster having the same stage of the disease and sharing the same degree of its severity. In other words, they typically adopted the binary classification by discrimination HCs vs PD patients. In this context, Zham et al. investigated the relationship between computed features on the spiral drawing and the severity of the disease. In particular, they studied the correlation between speed, pressure and the disease severity. As a result, they found a strong correlation by merging the two features, in consequence, they found accurate differences between early and advanced stage of the disease. Unfortunately, this approach was not capable to find differences between low and medium or medium and high level of the disease. Promising results were found in [111], by using angular features and number of direction changes while drawing the spiral.

Impedovo et al. have also investigated this issue [107]. They applied a classification study on the PaHaW dataset, concentrating only on low and medium degree of the PD severity. They show that the performances of the supervised learning techniques significantly decrease when they use this subgroup, rather than using all the PD patients acquired in the dataset which have more severe stages. Another contribution of this work, is the combination of the different tasks altogether, by merging the features computed on each task into one unique high dimensional feature vector.

Several studies investigate the efficiency of deep learning techniques [25, 83] given they automatic and accurate extraction of features. Generally, they use convolutional neural networks to feed the connected layers or only the standard classifiers. Unfortunately all the existing databases are small, however, various resampling methods are used to reach better and reliable performances of classification, namely the cross-validation technique and leave-one-out approach [50].

Similarly, Gallicchio et al. [67] adopted the application of deep learning techniques to early detect PD through on line handwriting by employing neural networks. These deep learning techniques were adopted in order to automatically extract relevant features without the human intervention from handwriting data of the ParkinsonHW dataset [48]. Successful results are reported in [48], where Mucha et al. suggest a new approach for computing kinematic features of PD patients relying on fractional derivatives of arbitrary order.

Authors in [44] improved the findings on the PaHaW dataset [30] by merging new features computed to velocity-based features with the classic ones. These features are computed through sigma-lognormal model, the Maxwell–Boltzmann distribution, and the Discrete Fourier Transform.

Similarly to the obtained results in [29, 87], Jerkovic et al. [65] show that in air and on surface strokes contain relevant and non-redundant information. Indeed, the best achieved accuracy resulted by merging both in-air and on-surface features.

In [60], Loconsole et al. used new features computed on the gyroscope signal provided by the digitizer tablet. Regrettably, they used a very small number of participants.

In another study, authors propose to compute geometrical and nonlinear dynamic features combined to standard kinematic features [84]. Rios-Urrego et al. aim at finding the abnormalities and irregularities of handwriting, which generally increase as the disease advances.

Besides, Diaz et al. [25] introduced a new "dynamically enhanced" representation of handwriting consisting of artificially generating images by exploiting at the same time static and dynamic properties of handwriting. Particularly, authors propose a static description that merge dynamic information relying on drawing points of the pattern, rather than linking them, in order to extract spatio-temporal and kinematic information with its relative pen-ups. This novel approach outperformed the findings already obtained by separating static from dynamic handwriting on the PaHaW database.

Ribeiro et al. [83] concentrated on the investigation of tremor as it is the most commonly symptom of PD. Specifically, they introduce to study the temporal information from time signals acquired from handwriting tasks based on the gated recurrent units included in neural network architectures. Besides, authors also proposed the novel concept of "bag of samplings" as a representation of handwriting signals.

In [3], Ammour et al. aim to use a clustering algorithm in order to analyze the intervention of several factors in the characterization of PD patients and HCs. These qualitative factors are: age, intellectual level, frequency of writing per week. Next, they used a semi-supervised approach on an Arabic imposed text. Authors computed the standard features in addition to new features calculated on pen inclination based on the azimuth and altitude angles provided by the digitizer tablet. The findings show three clusters: First cluster contains only PD patients, second one with mostly HCs, and the third one is a mixture between HCs with medium intellectual education level and PD patients with high intellectual level and writing frequency. This result indicates that education level may act as a resilience factor against the deterioration caused by neurodegeneration [4].

In [6] authors propose a novel method to detect Parkinson's disease, based on the segmentation of the online handwritten text into lines. Indeed, they propose to compare Parkinson's disease patients and healthy controls, based on the full dynamics of new temporal and spectral features. Three classifiers were used, K-Nearest Neighbors, Support Vector Machine and Decision Trees. The performances of these three classifiers were estimated using a stratified nested 10 cross-validation. An accuracy of 92.86% was obtained with Decision Trees classifier in the last line.

Starting from a Parkinson's disease database collected at Matarò Hospital in Barcelona, Randazzo et al. [82] present an analysis of a Parkinson's disease handwriting dataset in which neural networks are used as a tool for analyzing the problem space. They propose a comparative analysis about the classification performances of a multilayer perceptron (MLP) in order to determine the discriminative power of the selected features. They found fifteen temporal features, capable of a more meaningful discrimination with an upper bound performance of 100% and a final training error of 0.0004.

Besides, in order to detect PD through time series classification, Taleb et al. [95] investigate the application of the CNN and the CNN-BLSTM. The obtained results show that the accuracy reached 97.62% by combining CNN- BLSTM models trained with Jittering and Synthetic data augmentation approaches.

In [90], authors used a dataset consisting of 102 wave and 102 spiral handwriting patterns. The CNN model was trained and achieved an accuracy of 88%, 89%, and a sensitivity of 89%, 87% on the wave and spiral patterns respectively.

Finally, combining the age and sex information proved to be encouraging in [38] with an obtained classification accuracy over 83%.

In Table 5 a summary of all classification studies are presented. The classification methods used and the obtained results are also addressed.

6 Future directions

All of these previous studies have confirmed that Parkinson's disease has a major impact on the deterioration of handwriting's components. In addition, the realization of a Diagnosis Aid System (DAS) based on online handwriting involves an interaction between several technical aspects related to the choice of exercises, the choice of relevant parameters, the choice of methods of features selection, and classification. However, there are some other demographic, educational and medical factors related to the patient that can have a significant impact on the handwriting process. All of these factors must be taken into consideration while processing and analyzing manuscripts. The estimation of the degree of influence pertinent to these factors in presence of the disease could contribute effectively to improve the envisaged DAS's performances. Currently, none of the previous studies has provided any metadata for such an analysis [46]. Moreover, the extraction of the discriminant information may also depend on the graphic characteristics of the writing which vary according to the country and the language. Related works conducted on Parkinson's disease were particularly concerned with the Latin languages, and have only focused on words or sentences.

Further research can also investigate correlations between handwriting features, the Hoehn and Yahr scale, and the UPDRS to establish the use of handwriting analysis as a tool in clinical assessment.

Finally, it is worth mentioning all the research study conducted on handwriting should be extended to speech and gait with specific protocol for each modality. Thus, combining the

Table 5 Representation of classification studies conducted on handwriting of PD patients

References	Classification methods	Results
[32]	K-NN, AdaBoost, SVM	81.3% of accuracy obtained by SVM.
[30]	SVM, Naïve Bayes	88.13% of accuracy obtained by SVM.
[28]	SVM	80% of accuracy obtained by SVM.
[29]	SVM	84% of accuracy obtained by SVM.
[87]	Discriminant function	97.5% of accuracy obtained.
[2]	CNN	87% of accuracy obtained by CNN.
[71]	CNN	95% of accuracy obtained by CNN.
[54]	Naïve Bayes Classifier	91% of accuracy obtained by NB.
[44]	SVM with linear kernel	98.44% of accuracy obtained by SVM.
[60]	Optimal ANN, SVM	92.98% of accuracy obtained by SVM.
[6]	KNN, SVM, DT	92.86% of accuracy by DT.
[95]	CNN, CNN-BLSTM	97.92% by combining CNN- BLSTM models
[90]	CNN	89% of accuracy by CNN.
[38]	SVM	83.75% of accuracy by

promising results with those of speech and gait could help to detect the neurodegenerative diseases at an early stage.

7 Conclusion

In conclusion, the field of handwriting analysis in order to diagnose Parkinson's disease has experienced a plethora transformation after the introduction of kinematic and spatio-temporal analysis using the technology of digitizing tablets and smart pens BiSP.

Overall, on line handwriting can be considered as a good biomarker for the monitoring of PD. This chapter aimed at providing a clear overview of the various studies conducted on handwriting analysis in order to develop an early and reliable diagnosis aid system capable of monitoring and assessing PD, starting by handwriting data acquisition, feature extraction and data analysis and classification. The main findings to retain are: PD patients undergo several irregularities and abnormalities in their handwriting such as micrographia, jerking and slow movements.

Besides, we give a sight on the still opening issues in this research field that need to be addressed, because even if all the presented studies have proved the efficiency of online handwriting in the assessment of PD, they still confront various challenges.

For instance, the protocol definition is an open problem that requires to be investigated. Researches should find which task can be more accurate to discriminate at best between PD patients and HCs.

Declarations

Conflict of interest The author declares no conflict of interest.

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