Wearable sensors and features for diagnosis of neurodegenerative diseases: A systematic review

Huan Zhao[1] iD , Junyi Cao[1], Junxiao Xie[1], Wei-Hsin Liao[2], Yaguo Lei[1], Hongmei Cao[3], Qiumin Qu[3] and Chris Bowen[4]

Abstract

Objective: Neurodegenerative diseases affect millions of families around the world, while various wearable sensors and corresponding data analysis can be of great support for clinical diagnosis and health assessment. This systematic review aims to provide a comprehensive overview of the existing research that uses wearable sensors and features for the diagnosis of neurodegenerative diseases.

Methods: A systematic review was conducted of studies published between 2015 and 2022 in major scientific databases such as Web of Science, Google Scholar, PubMed, and Scopes. The obtained studies were analyzed and organized into the process of diagnosis: wearable sensors, feature extraction, and feature selection.

Results: The search led to 171 eligible studies included in this overview. Wearable sensors such as force sensors, inertial sensors, electromyography, electroencephalography, acoustic sensors, optical fiber sensors, and global positioning systems were employed to monitor and diagnose neurodegenerative diseases. Various features including physical features, statistical features, nonlinear features, and features from the network can be extracted from these wearable sensors, and the alteration of features toward neurodegenerative diseases was illustrated. Moreover, different kinds of feature selection methods such as filter, wrapper, and embedded methods help to find the distinctive indicator of the diseases and benefit to a better diagnosis performance.

Conclusions: This systematic review enables a comprehensive understanding of wearable sensors and features for the diagnosis of neurodegenerative diseases.

Introduction

The number of patients affected with neurodegenerative diseases (NDDs) increased rapidly in the last few decades, which brings an adverse impact on society and the economy.[1] In general, NDDs include Alzheimer's disease (AD), Parkinson's disease (PD), multiple sclerosis (MS), amyotrophic lateral sclerosis (ALS), and Huntington's disease (HD). NDDs tend to be progressive, and there is no cure for most of them. Accurate diagnosis of NDDs as

[1]School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an, P.R. China
[2]Department of Mechanical and Automation Engineering, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong, China
[3]Department of Neurology, The First Affiliated Hospital of Xi'an Jiaotong University, Xi'an, P.R. China
[4]Department of Mechanical Engineering, University of Bath, Bath, UK

Corresponding author:
Junyi Cao, Xi'an Jiaotong University, 28 Xianning West Road, 710049, Xi'an, P.R. China.
Email: caojy@mail.xjtu.edu.cn

early as possible can help patients to obtain preventive measures even before the occurrence of irreversible brain damage.

Each NDD is heterogeneous in clinical representations, though there are often overlaps.[2] Symptoms of NDDs on motor behavior are as follows[3]: AD has hypokinesia, apraxia, and abnormalities in walking and trunk movements[4]; PD displays the symptoms of resting tremor, rigidity, bradykinesia, and postural instability,[5] and the bradykinesia also existed in eye movement[6]; MS shows motor weakness, spasticity, ataxia, and sensory disturbance[7]; ALS has the perturbations in the fluctuation dynamics, altered gait rhythm, weakness in legs, feet, or ankles[8]; HD has uncontrolled movements, emotional problems, psychiatric disorders, and loss of thinking abilities.[9] Moreover, depression symptoms,[10] motor disorders,[11] as well as speech alterations are common in NDDs.

Evaluation of health state and diagnosis of NDDs in most clinics today still rely on the observation-based assessment by clinicians. Thus, the measurement-based diagnosis and treatment of NDDs have attracted interdisciplinary research interest. The objective diagnosis approaches of NDDs are mostly based on neuroimaging, cognitive performance tests, language features, molecular and genetic data, neurophysiological and morphological biomarkers, and clinical records.[12,13] Utilizing a simple and reliable wearable system provides a possibility for predicting NDDs in daily life. In addition, both the lack of resources for face-to-face medical facilities and the COVID pandemic requires the remote diagnosis and monitoring of patients with NDDs in daily life.

Wearable sensors are widely employed for their lightweight, non-invasive, and real-time monitoring-supported abilities.[14] They provide objective, accurate, and reproducible measurements that can complement the use of traditional methods.[15] Based on data collected from wearable sensors, machine learning methods were applied for the detection of pathologies.[16] Thus, the recent advances in wearable sensors for biomedical applications[17,18] promise smart portable, ingestible, and implantable devices for human health monitoring and disease management.[19]

The wearable data were illustrated by the features for the final diagnosis of NDDs.[20] Wearable sensors applied to PD for early diagnosis at home and long-term monitoring were achieved by features from tremors, body motion analysis, and motor fluctuations (ON–OFF phases).[21] Handwriting analysis to support the diagnosis of AD, PD, and mild cognitive impairments was organized by modeling, tasks, and feature analysis.[22] During these mentioned diagnoses, features were extracted from the wearable data, and then the distinctive features were selected to feed into the traditional machine learning model to diagnose the health state. With the selected features, the performance of traditional machine learning can be improved since features that are irrelevant, redundant, or noisy are eliminated.

Prior reviews focused on either wearable sensors, diagnosis methods, or specific diseases, respectively, while the process of how and what features are extracted and selected from different wearable sensors for the diagnosis of NDDs has not been reviewed systematically. Accordingly, the primary objective of this systematic review is to screen the current studies and provide a comprehensive understanding of different wearable sensors and their feature extraction and selection for the diagnosis of NDDs. Therefore, three specific questions were addressed: (1) What kinds of wearable sensors are most frequently used in NDDs diagnosis? (2) Which features are developed for the recognition of NDDs? (3) How features are selected for the efficient diagnosis of NDDs?

Method

Search strategy

This review was conducted following the PRISMA statement guidelines.[23] Though a protocol for this study has been prepared internally, it has not been registered elsewhere, and the PROSPERO database has been checked to confirm the originality of the study.

Electronic searches on the Web of Science, Google Scholar, PubMed, and Scopes were performed. The database searches were completed in September 2022. Searched examples included: "neurodegenerative disease," "diagnosis," "wearable sensors," "feature extraction," and "feature selection." The defined search duration includes articles published between 2015 and September 2022. Additional studies were also identified by the reference lists of articles.

Eligibility criteria

The identifying, screening, and selecting of studies for inclusion were conducted as shown in Figure 1. To be identified for inclusion, studies needed to meet the following criteria: they had to be original research written in English, and published in a peer-reviewed journal or conference. Titles and abstracts were screened and excluded if they: (a) were not relevant to the topic; (b) were duplicates; and (c) were similar to selected studies. Then the full texts of the identified studies were screened and studies that used unwearable sensors and without features were excluded. Finally, the studies were excluded if they use the same sensors and features. Each reviewer independently assessed or validated the selected studies. The entire process was carried out manually, without the use of any automation tools.

To provide a comprehensive overview of wearable sensors and their features for the diagnosis of NDDs, the obtained papers were reviewed and organized in the way of a computer-aided diagnosis process as shown in Figure 2. Various wearable sensors collect different
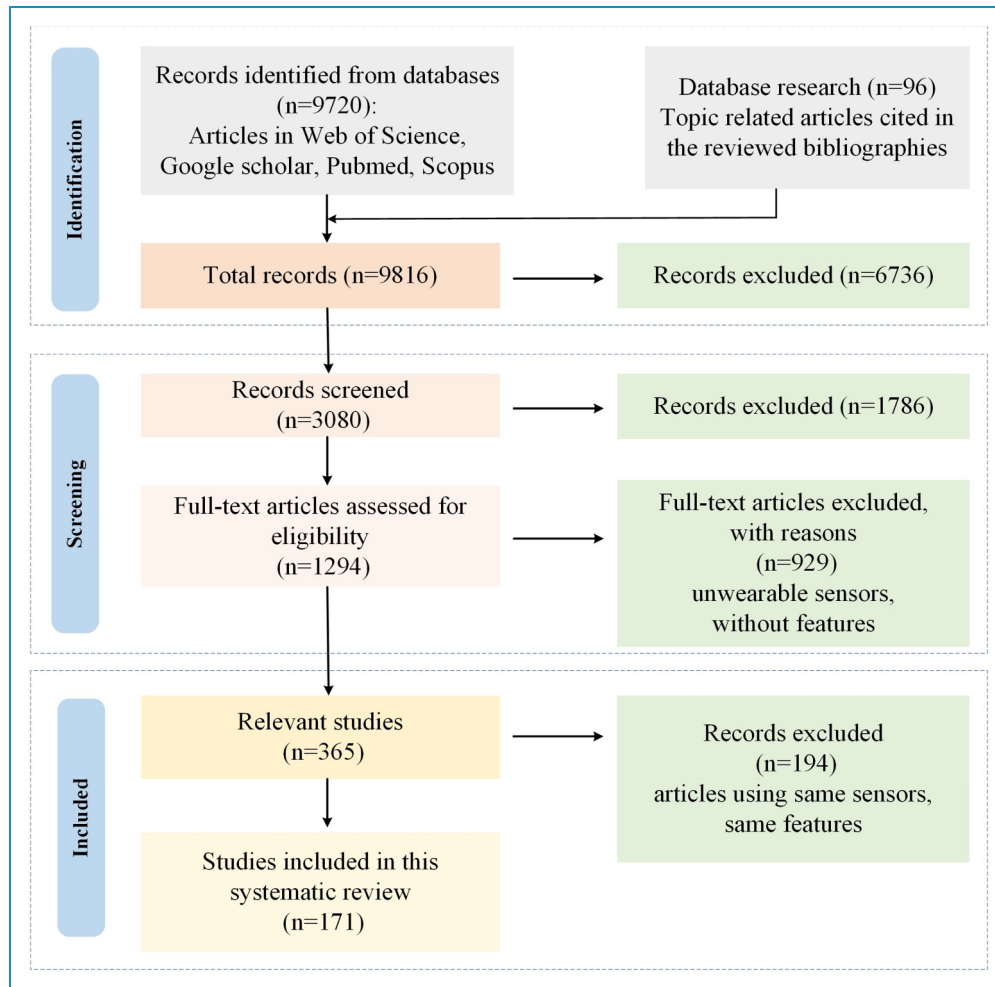
Figure 1. The flowchart of the study selection process.

types of data, and from these data, the features are extracted and then selected, finally the selected features are inputted into the machine learning model to recognize the health state.

Results

Wearable sensors and their application for NDDs diagnosis

Wearable sensors are generally placed on different parts of the human body that do not hinder natural movement, and the captured data are transmitted through wireless connections or collected on onboard storage devices. With the rapid development of electronics, biocompatible materials, and nanomaterials, wearable devices have evolved in the form of accessories, integrated clothing, body attachments, and body inserts.[24,25] As for NDDs diagnosis and monitoring, various types of sensors can be applied to completely and continuously obtain human activity signals such as

plantar pressure, lower limb posture,[26] joint bending,[27] and so on [28] as shown in Figure 3.

Pressure and strain sensors. Wearable force sensors are flexible or with a flexible substrate to impart mechanical stability to the active material. Force sensors are divided into pressure and strain sensors due to the applied compression or tensile. The transform principles of pressure and strain sensors are diverse such as piezoresistive, piezoelectric, capacitive, and triboelectric.[29]

Piezoresistive sensors. Piezoresistivity transforms the mechanical deformations caused by the applied pressure or strain to electrical resistance variations. As a typical piezoresistive pressure sensor generally used, force-sensitive resistors (FSRs) are ultra-thin, low-cost, pressure sensors. FSR can be used in biosignal acquisition for the diagnosis and monitoring of disorders.[30] It can be embedded in gloves to measure both the frequency of the tapping and the force that patients applied in grip.[31] FSR was generally in the shape of radial since the circular
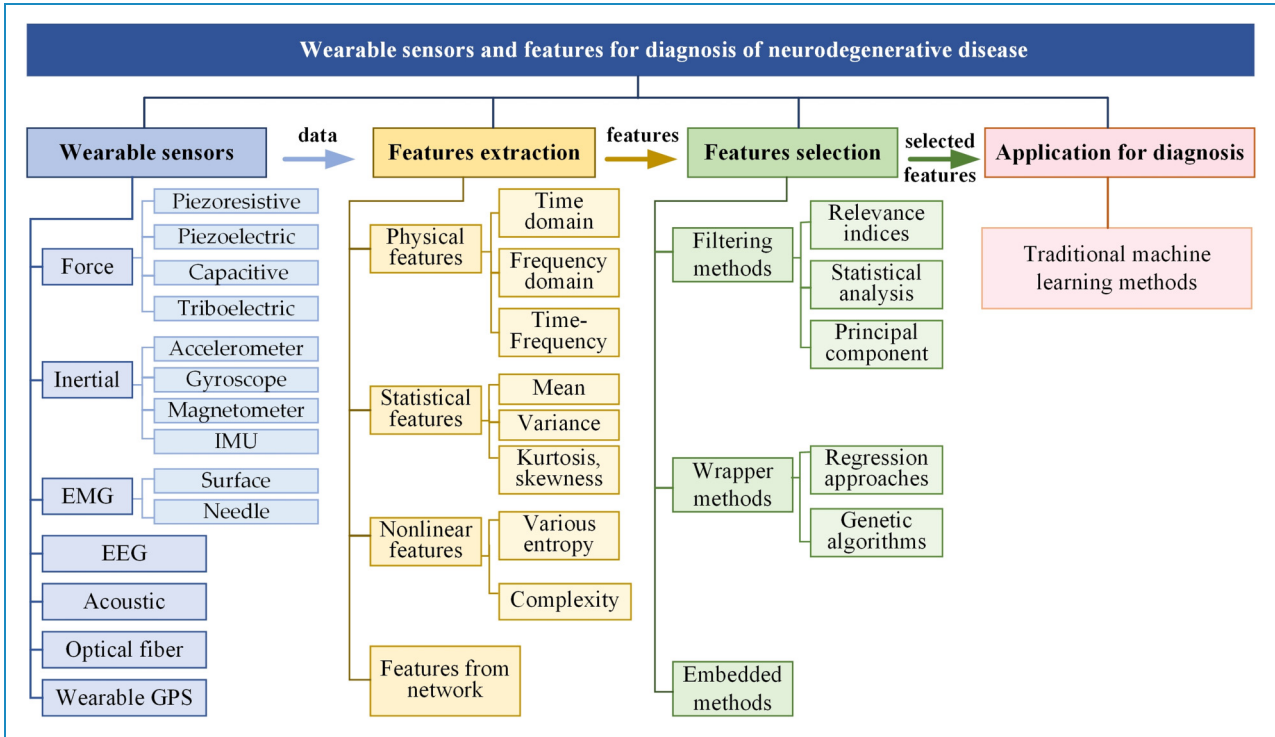
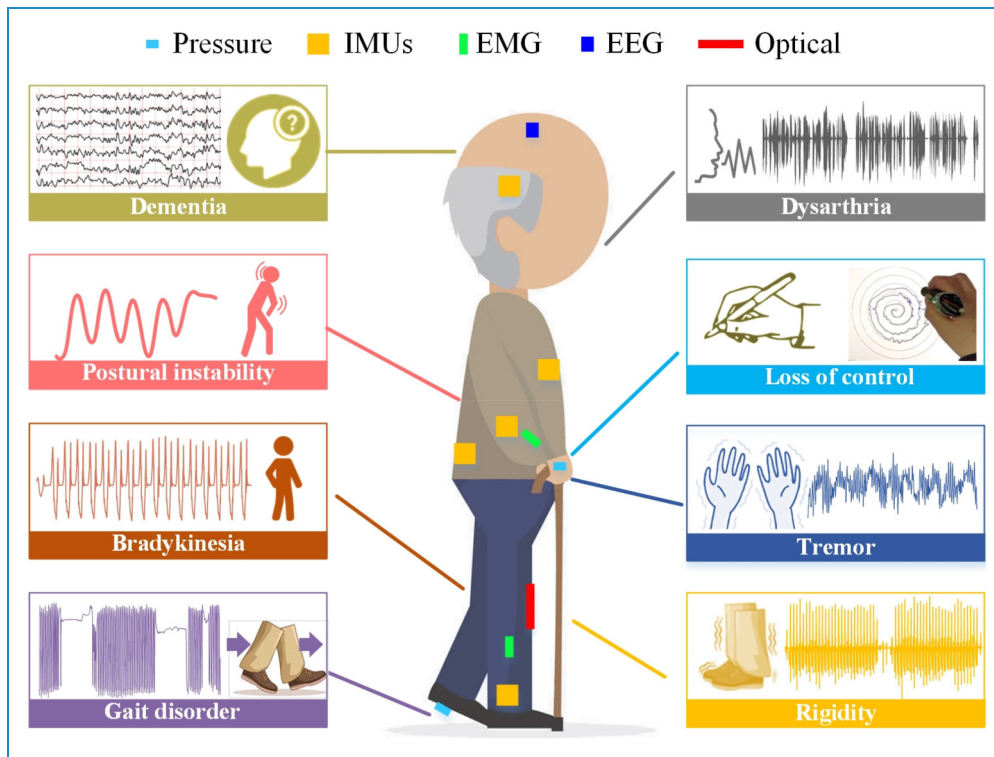**Figure 2.** The diagnosis process using a wearable system with detailed methods.

Figure 3. Wearable sensors applied to the human body for neurodegenerative diseases (NDDs) diagnosis.

structure sensor is most suitable for foot pressure measurement. The irregularity of vertical ground reaction force (vGRF) signals of NDDs caused by gait abnormalities can illustrate different force pattern variations compared to healthy controls (HCs),[32] and thus gait analysis can be used for the diagnosis of NDDs.[33]

Piezoresistive strain sensors were successfully applied for measuring bending and torsion types of motion such as knee movement, hand gesture, breathing, phonation (speech), elbow bending angle, finger bending, wrist bending, eye blinking, and neck movement.[34] Plantar pressures with different NDDs and severity levels were given in a public dataset named Physionet (www.physionet.org).[8,35] One contains the vGRF of different parts of the plantar from 93 patients with idiopathic PD and 73 HC subjects. Another one contains the total vGRF from 20 HD patients, 13 ALS patients, 15 PD patients, and 16 HC subjects. These data were collected when the subjects walked on level ground at their preferred speeds. It is easy to acquire heel strike and toe-off moments, then the gait events and even more complex features can be deduced for NDDs diagnosis.

Piezoelectric sensors. Piezoelectricity is when the material is compressed and deformed, the cationic and anionic are separated from center to surface, thus positive and negative charges are accumulated on the electrodes and produce electrostatic potential. Polyvinylidene fluoride (PVDF) could exhibit a relatively high piezoelectric property after polarization at a high temperature, and it is widely studied due to the impact of piezoelectricity on biological systems and their versatile biomedical applications. It can be used not only for long-term and stable energy supply but also to monitor a variety of vital signs such as heart rate, breathing, and blood pressure.[36,37] As for motor abnormality detection, PVDF sensors were arrayed in insoles to collect plantar pressure in real time.[38] Since the plantar bend of NDD patients tends to be different from the HC, PVDF strips were taped at insoles to measure plantar bend and impact force for NDDs monitoring.[39] Because of the wide application of piezoelectric and piezoresistive sensors in measuring plantar pressure, their wearable gait monitoring techniques were compared.[40]

Capacitive sensors. A capacitive sensor composes of dielectric material sandwiched between two electrodes or a structured air gap in the middle of the two electrodes. The electrical energy is stored by transforming it into the electrostatic field. It is widely applied in knee jerks, joint movements, wrist and finger bending, throat motion, and so on as reviewed in Homayounfar and Andrew.[34] Moreover, stretchable and wearable capacitive electrophysiological sensors are applicable for long-term health monitoring.[41]

As for diagnosis and monitoring application to NDDs, capacitive sensors also have potential. A capacitive eye tracker was developed to monitor eye movement. This hybrid capacitive sensor made of fibrous and rectangular electrodes had the highest sensitivity since the initial capacitance was reduced and capacitance change was increased when the eyeball was presented.[42] Since PD has abnormal eye movement, this device can be applied to diagnosis and monitor of PD.

Triboelectric sensors. Triboelectric sensors transform mechanical deformation to electricity through the triboelectric effect, which is contact electrification followed by electrostatic induction. Except for the application in cell modulation, drug delivery, circulatory system, hair regeneration, neural prosthesis, biodegradable electronics, gene delivery, microbial disinfection, and implantable devices, TENG is employed for healthcare monitoring by heart and respiratory monitoring, joint motion sensing, sweat and gait phase detection, hearing aid, throat phone, and CO_2 detection.[43] Triboelectric transducers which are alternative stretchables and sensitive to muscles/tendons movements were placed on the forearm for PD monitoring by examining not only tremor but also bradykinesia and rigidity same as required by the Unified PD Rating Scale (UPDRS).

Inertial sensors. As motor symptoms predominate and cause considerable functional impairment in patients with NDDs, quantifying gait, and postural control helps the understanding of neurological conditions. Therefore, accelerometers, gyroscopes, and inertial measurement units (IMUs) were widely employed.[44]

Accelerometers. The accelerometer measures the acceleration of objects. For NDDs diagnosis by postural measurement of the whole body, the progression markers in the premotor phase of PD were investigated by an accelerometer placed at the back.[45] An accelerometer can also be placed at the center of mass at the lower spine to quantify the sway during a quiet stance with eyes open and closed for the detection of prodromal PD.[46] Accelerometers attached to hips and ankles can be used in gait and balance assessment, and the results show that dual-tasking will help dissect the cognitive and motor contribution in mobility and cognitive decline and future adverse outcomes including falls and mortality.[47] Linking acceleration gait measures to motor skills of walking proved useful in quantifying declines due to aging and other neuromotor factors.[48] Absolute fall incidence was high in NDDs, thus an accelerometer measuring physical activity such as lying or sitting, standing, and walking was used to figure out the fall risk.[49] Especially, an accelerometer-based system that records acceleration signals in 3 dimensions (3D) for intelligent fall detection was developed and it was fastened to the subject's chest.[50]

For local part measurement, an accelerometer equipped at the middle finger was far more accurate than at the thumb and center hand to diagnose the stage of PD since the intensity of the PD is related to the amplitude of tremor signals.[51] A wrist-worn accelerometer with the

support of a disease-specific cut-point may be further used to measure activities across the continuum during 24 h period in PD.[52] A wireless accelerometer applied with iPhone was used to characterize the tremor of PD.[53] A smartphone accelerometer placed at the wrist using a random forest classifier achieved a high diagnosis accuracy of PD, but moderate accuracy of essential tremor (ET) and poor accuracy of dystonic tremor.[54] Accelerometers can also be tapped at the neck to differentiate between swallows from healthy people and people with NDD.[55] Moreover, it can be employed in handwriting analysis.[56] A device based on an array of four accelerometers connected to an embedded development board was developed to monitor tremor/movement and accidental falls, it can track the Alzheimer subjects' geographical position.[57]

Gyroscope. A gyroscope measures angular velocity or acceleration, and it is sensitive to shocks. It can be employed to detect the tremor at the finger, hand, wrist, and so on. A gyroscope mounted on the hand or head can acquire the tremors since tremulous rotation at the wrist, elbow, or neck will induce tremors.[58] By evaluating angular velocity data recorded by mobile phones' built-in gyroscope, HC, PD, and ET can also be differentiated.[59] The gyroscope equipped on the shank with a standard deviation algorithm was also developed to prevent falls of PD patients.[60]

Magnetometer. The magnetometer can find the orientation of an object by measuring the earth's magnetic field. The bio-magnetometer can enhance the image and eliminate the limitation of conventional magnetoencephalography.[61] In human motion measurement, the magnetometer usually appeared with an accelerometer and gyroscope together.[62] Since the magnetic disturbances contained the magnetometer data for indoor applications, a linear Kalman filtering-based magnetometer-free sensor had been designed for motion capture.[63]

Inertial measurement unit (IMU). IMU is a combination of accelerometers, gyroscopes, and occasionally magnetometers, thus it can calculate the angle, velocity, orientation, and gravitational force of the subject. IMU was utilized for gait analysis generally, instrumented clinical tests, upper body mobility assessment, daily-life activity monitoring, and tremor assessment.[64] Wearable IMU has become a solution with the advantage of higher sensitivity and specificity for remote health monitoring since it can not only assess the movement disorders induced by NDDs, but also can evaluate frailty and falls, and promote active living.[65]

IMU consists of an accelerometer, gyroscope, and magnetometer incrusted in an ergonomic glove equipped with a module for a micro SD card and Bluetooth adapter. It is portable and wireless with mobility acceptable to the user when testing in different environments.[66] IMU composed of a triaxial accelerometer, a gyroscope, and a magnetometer was placed at the feet dorsum, shanks, thighs, chest,

and the back side on the lumbar zone for PD diagnosis. Results indicate that diagnosis accuracy does not directly relate to sensor number.[67] IMU placed at a subject's lower back with gait parameters estimating algorithm can be used for quantifying the progression of PD and assessing medication administration.[68] Four IMUs were attached to the subject's lower limbs to obtain continuous relative phases for distinguishing PD and PD group division.[69] Moreover, to supplement the electrooculogram sensor that measures the eye movement for early diagnosis of NDDs, IMU sensors were embedded in an eyeglass to measure the head movement and tremors.[70]

With the development of smartphone techniques, smartphones can provide an inexpensive measurement platform with built-in sensors (acceleration and gyroscope) for health state assessment. For example, accelerometer and gyroscope data collected from a smartphone can be used for PD detection.[71] It can be attached firmly to the subject's waist in a bag during a 20-step walking test.[72]

Electromyography sensors. Electromyography (EMG) signal is the electrical current generated in muscles during neuromuscular activities, and it indicates the degree of muscle activation and fatigue. Surface EMG is the non-invasive electrodes applied on the skin, and it is affected by the noise from the nearby muscle. The fine wire electrode is more accurate and precise since it is inserted into the muscle using a hypodermic needle, thus it is also called needle EMG.[73] Surface EMG provides significant practical and analytical flexibility compared to invasive techniques in ALS.[74] It was widely employed in the diagnosis of NDDs by sleep disorders, motor (gait, posture, facial expression, and handwriting) impairments, and other biomarkers. The EMG signals of antagonist muscles surface can investigate PD patients, ET patients, and HC.[75] To obtain an accurate diagnosis of gait disorders, 10 bipolar surface EMG electrodes were attached to five muscles of each leg.[76]

Surface EMG signals from the upper extremities, such as the arm and wrist, would be an efficient way to assess neuromuscular function in the detection of PD.[77] To classify different severity levels of PD, surface electrodes were placed over flexor carpi radialis and biceps brachii muscles to record EMG signals during selected upper arm movements: elbow flexed at 90°, elbow flexed at 90° with 1 kg load, wrist pronation, and touching the shoulder.[78] High-density surface EMGs at the vastus lateralis muscle were collected when the participants performed ramp-up and sustained contractions at 30% of their maximal voluntary contraction and then decomposed into individual motor unit firing behavior using a convolution blind source separation. This is an important physiological index for understanding the pathophysiology of ALS.[79]

In addition, surface EMG sensors were also employed for NDDs diagnosis in some tasks. The UPDRS can be predicted by surface electrodes of EMG attached to a wristband

in a tapping task.[80] EMG signals from eight different points of the forearm during handwriting were acquired by the Myo™ Gesture Control Armband (www.myo.com) for the PD diagnosis.[56]

Tonic but not phasic EMG activity may serve as stable biomarkers for predicting the progression of neurodegeneration in idiopathic rapid eye movement (REM) sleep behavior disorder.[81] Assessed by excessive transient muscle activity in the chin or limb EMG in REM sleep, idiopathic REM sleep without atonia may be accepted as a risk factor in the development of PD or other types of NDDs.[82] It is worth mentioning that when EMG was used with transcranial magnetic stimulation to measure the invoke muscle responses, robust measures of function in a variety of cortical network components will be measured.[83]

Electroencephalography sensors. Electroencephalography (EEG) was collected by sintered Ag/AgCl electrodes attached to the scalp. EEG signals contain rich information related to the functional process of the brain. It promised to study the relationship between functional impairment and the neural circuit. The influences of PD on brain activity differ from the healthy person's activity.[84]

The EEG for NDDs diagnosis was generally collected during resting state [85] with the eyes open or closed to reduce the influence of noise related to artifacts such as blinks, heartbeats, cranial muscle activity, and electrode movements caused by head movements.[86] With the miniaturization of EEG equipment, portable wireless headsets sprout and it helps the utilization in daily life activities.[87]

There are many public EEG datasets collected from NDD patients. University of California San Diego Resting State EEG dataset recorded 15 PD patients and 16 HC subjects.[88] EEG signals from 25 PD patients and 25 HC subjects were recorded during a three-stimulus auditory oddball paradigm both with and without medication.[89] Neuronetrix dataset collected the EEG signal from 103 subjects with probable mild AD and 101 HC subjects under clinical tests.[90]

Acoustic sensors. Abnormal voice patterns indicate the health state to some degree. For example, PD patients lack intensity modulation,[91] while the progression of HD relates to speech alteration.[92] Acoustic analysis is a valuable and objective tool supporting the diagnosis of NDDs, especially in remote medical examinations during pandemic durations. For capturing voice and speech signals, microphone sensors are appropriate since they are tiny, low-cost, portable, and readily configurable with embedded electronics. An omnidirectional microphone was utilized to collect phonation of sustained vowels /a/, /e/, /i/, /u/ from 39 HC subjects, 60 patients affected by PD, and 54 patients affected by MS.[93] The bulk acoustic wave or quartz crystal microbalance was also employed for breath analysis

in NDDs.[94] The speech acoustic and articulatory movement data were collected by electromagnetic articulagraph attached to the subject's tongue, lips, and head, and they could improve the performance of ALS detection significantly.[95]

Except for speech signals, body sounds (e.g. breathing, clearing throat, and swallowing), which can be collected from the subject's phone usage (e.g. calling, voice message, voice mailbox, and voice chatting) in daily life can also assess the health condition using a customized residual network.[96] Smartphones may provide an increasing number of longitudinal vocal samples from a given individual in an easy and inexpensive way.[97] It has been proved that PD can be predicted early even through voice recordings recorded on smartphones.[98] Voice signal collected from the smartphone can be conveniently uploaded and then transmitted to the cloud, and the noise and size of the signal were reduced to store as history information. Experts or doctors can then detect and monitor patients from remote areas.[99]

There are some acoustic datasets such as the dataset from the University of California at Irvine Machine Learning Repository. The data were collected from 20 healthy individuals and 20 patients with PD.[100,101] DementiaBank contains speech data from 167 AD and 97 HC subjects.[102]

Optical fiber sensors. Though optical array sensors are highly advantageous for the early detection of AD with multi-biomarkers,[103] it is chemical and not wearable. Optical fiber sensors are developed based on the change in light transmittance as follows: the light beam generated by a light source travels through an optical fiber, and then the intensity-attenuated light beam is received by a photodetector. By simple calculation of the light intensity attenuation, the bending angle of the optical fiber can be obtained, thus it can monitor the human joint angle.[104] Since optical fiber sensors are stretchable and highly sensitive, they were assembled into clothing or mounted on skin surfaces for monitoring human activities such as wrist pulses, joint bending, and hand gestures.[105] In addition, it can even non-invasively quantify the analytes or physiological events under the skin.[106]

Optical fiber Bragg grating (FBG) sensors attached to the biocompatible tape were used to monitor the knee angular flexion/extension during walking, and it is even possible to detect the muscle's peak activity moments.[107] Moreover, the sensing network of FBG sensors was multiplexed (in series) in one single optical fiber cable, thus it can simultaneously monitor plantar pressure, peak muscle activity, and the ankle and knee sagittal range of motion, without the need for any synchronization or delay adjustments.[108] Though optical fiber sensors emerged in recent years, their application in joint bending and activity monitoring can be further put into use in the diagnosis and monitoring of NDDs.

Global positioning system. Global positioning system (GPS) and similar technologies in commercial wearable devices such as smartphones, navigation systems, and smart watches can collect precise locations at any time, thus they can assess daily mobility patterns.[109] Though there is a paucity of published studies about wearable GPS, some NDDs-related work had been conducted. Wearable GPS-derived measures had been validated and may apply to NDDs.[110] Wearable GPS was also compared to self-reported measures in recording mobility outcomes and proved promising for research and clinical measure of real-life mobility in PD patients [111] and healthy older adults. The mobile phone's built-in GPS distinguished mild-to-moderate AD patients from controls.[112] Moreover, GPS driving may serve effectively for identifying preclinical AD among older adults.[113]

Multi-sensors. These mentioned wearable sensors have different applications, strengths, and drawbacks as shown in Table 1. To take full advantage of these sensors and acquire more NDDs-related information, multi-sensor systems have been devised and tested for NDDs diagnosis propelled by the development of integrated electronics. The sensor network with a complex array is better suited to the diagnosis of PD while the arrangement can be simplified for quantification and tracking once the diagnosis is determined.[114] The combination of EMG and EEG signals can achieve the highest diagnosis accuracy than they singly used.[115] It was observed that heterogeneous sensor-based health monitoring is the most effective way because of its ability to combine multiple sensors from various domains. This also indicates that the fusion of multiple sensors provides reliability, credibility, and better accuracy for human health monitoring by multiple parameters.[116] Versatile wearable sensors can be integrated into smartphones, tablets, smart watches, eyeglasses even masks facilitated to healthcare in daily life.

Features extraction

Features are the key to distinguishing the type of NDD, it also determines the classification performance. To illustrate the underlying differences between NDDs and HC as well as the differences among NDDs themselves, various kinds of features were extracted as displayed in Figure 4.

Physical features. *Time domain features.* Physic-related features that can directly illustrate the appearance of the motion are extracted from the time domain. There are many different physical features on the account of the versatile signal obtained by various sensors.

Several gait features that characterize vGRF patterns were extracted including gait duration, peak value, and peak delay.[117] Spatiotemporal gait features indicate time and distance-related gait events, for example, the stride time, stance time, swing time, step length, stride length, gait speed, and cadence.[118] Step velocity and step length were found to be the best and most stable gait characteristics defining progression during the prodromal PD phase. Moreover, the asymmetry of step, swing, and stance time and step length are higher for PD patients than HC.[119] The speed, stride length, swing time, and hip excursion were found reduced in patients with PD compared to HC during normal walking. Additionally, PD patients presented higher cadence and double support time.[5] The postural sway can also be characterized by: total sway area and 95% ellipse sway area. While anticipatory postural adjustment was represented by durations, first-step length (degree), and first-step latency.[120] The amplitude and peak-to-peak value of the plantar bend signal were found lower for PD patients than HC.[39]

Range of motion refers to the minimum to the maximum angle between two adjacent articular segments within one gait cycle. Range of motion of the ankle, knee, and hip was found reduced for PD patients, and they help to higher diagnosis accuracies when combined with spatiotemporal features.[67] The estimated tremor amplitude showed a high correlation to the UPDRS subscores.[121]

Execution time is the time interval(s) during the handwriting task, it can be extracted from the EMG signal with the adaptive threshold. This dynamic feature was important to different PD patients from HC.[122] The motor unit number index of limb muscle for ALS patients was found consistently lower than HC, while the muscle fiber conduction velocity was increased in ALS.[74]

When tackling dysarthric-like speech of NDDs, duration of pause intervals, rate of speech timing, articulatory rate, change in interval length, period of onset of vocalization, and vowel keeping time were extracted.[123]

As for GPS data, features such as "hourly frequency" (number of trips taken outside of the home per hour sampled) and "daily duration" (percentage of total time sampled per day individuals were outside of the home) were significant.[111] Location and activity features are active time ratios, steps per recording, time at the home ratio, trips out, destination trips, and max distance; transit and community mobility features are distance or time in the vehicle, distance or time on foot, ellipse max distance or area.[113]

Frequency domain features. Frequency analysis completes the information of time domain features. Frequency spectra (obtained by fast Fourier transform) and power spectral density of left stride, right stride, and left swing signals, which were derived from the vGRF signal were effective to differentiate patients with ALS, HD, or PD from HC subjects.[124] Features of power spectral density such as peak amplitude, peak delay, and area under the curve were extracted.[117] Higher-order spectra have the ability to preserve useful information due to deviations

Table 1. The sensors used for diagnosis of NDDs.

Sensors	Principle/kind	Positions	Applications	Strengths	Drawbacks
Pressures/ strain sensors	Resistance change	Planta, finger, radial artery, waist, thigh, shank	Phonation (speech), breath, joints movement, and bending	Flexible, easy-to-acquire gait features	Poor temperature characteristics
	Piezoelectric effect	Planta, finger, joints, limbs	Artery pulse, joint or limb bending, respiration	Superior dynamic response ability	Can't sense the static force, influenced by temperature change
	Capacitance change	Finger, hand, wrist, elbow, knee	Tactile pressure, joints movement	Stable to temperature	Poor load capacity, nonlinear output
	Triboelectric effect	Hand, knee, arm	Sleep monitoring, respiration, and joint angle	Efficient transformation	Easy to wear and tear
Inertial sensors	Accelerometer	Hand, back, waist, limbs	Tremor analysis	Non-invasive with minimal participant preparation time, cheap	Rigid, requires complex algorithms, sensitive to shock, free-living measurements may be limited
	Gyroscope	Finger, hand, wrist,	Detect tremor and bradykinesia	Free of gravitational artifact	Sensitive to gravity and linear acceleration
	Magnetometer	Same with others	Combined with an accelerometer and gyroscope	Tolerant to noise	Contained by magnetic disturbances
	IMU	Limbs, waist, head, hand, ankle	Detect falls, tremors, and bradykinesia	Cheap, stable	Offsets, zero drift, rigid
EMG	Surface EMG	Muscles of limbs	Detect muscle activity, muscle force	Non-invasive	Effect by near muscles
	Needle EMG	Muscles of limbs	Detect muscle activity	Precise	Invasive
EEG	Potentials of the cerebral cortex	Scalp	Describe cognitive activity	Strong adaptability, cheap, non-invasive	Sensitive to noise
Acoustic	–	Near lip	Phonation (speech)	No burden	Environment noise
Optical fiber	–	Joints	Detect joints bend	Immunity to electromagnetic noises	Low sensitivity, expensive
GPS	–	Mobile phone, smart watch, vehicle	Mobility, hour frequency and daily duration outside home, life space size	Precise, objective for position obtaining	Need longer battery lives

NDD: neurodegenerative disease; IMU: inertial measurement unit; EEG: electroencephalography; EMG: electromyography; GPS: global positioning system.

from Gaussianity and nonlinearities in the time series such as EEG and EMG.[125]

EEG signals either for AD or HD detection were analyzed by Fourier transformation. AD patients display a slow characteristic EEG frequency band than HC.[123] The average magnitude of the fast Fourier transform coefficient extracted from the EEG signal can classify AD patients from HC participants, and it gains new insights into how the location of channels and frequency bands correlate to AD classification accuracy.[126]

When comes to the speech signals, the main frequency of vocal cord vibration or pitch, jitter, shimmer, noise-to-harmonics ratios, formant frequencies, pitch and amplitude perturbation quotient, Mel frequency, and cepstrum coefficient were extracted.[123]

Time-frequency domain features. Time-frequency analysis is a generalization and refinement of Fourier analysis. Continuous wavelet transform, short-time Fourier transform, and wavelet synchro squeezed transform were applied to obtain time-varying frequency spectrum characteristics based on a vGRF signal.[32] The six-level discrete wavelet transforms with different wavelets were employed to extract detailed components of force signals for both left and right feet for the NDDs classification.[127] Using wavelet coherence to the visualized time-frequency spectrogram of plantar force signals helps to differentiate between the gait phenomenon of patients with NDD and HC.[128] Intrinsic mode functions calculated by empirical mode decomposition have been extracted for PD detection based on the Euclidian distance of vGRF signals after phase space reconstruction.[129]

The local maxima of the wavelet spectrum from EMG and acceleration data at the tremor side in the 1–3 Hz and 3–7 Hz frequency bands are promising for the early diagnosis of PD.[130] Mel-frequency cepstral coefficients and the tunable Q-factor wavelet coefficients obtained from voice signals achieved high accuracy when classifying PD patients and HC.[131]

Statistical features. Statistical features describe the statistical characteristics of signals. Traditional statistics such as mean, standard deviation, skewness, and kurtosis can deal with the time domain features and frequency domain features further for more distinctive markers.

To identify distinct features of PD gait, the mean, standard deviation, and even coefficient of variance (the ratio of standard deviation to the mean) of physical features were extracted.[132] Step width variability was found significant for the diagnosis of PD, while stride width variability and step double support time variability were found related to the PD severity level.[133] The longitudinal assessment of gait impairments found that gait variability and asymmetry characteristics seem to be the best predictors for PD conversion. For example, higher step time variability and asymmetry of all gait characteristics were associated with a

shorter time to PD diagnosis in Del et al.[119] On the contrary, a lower variability of wrist movement was found compared to HCs.[134] Mean, variance, skewness, and kurtosis based on sparse matching pursuit decomposition of vGRF were found more efficient in ALS detection.[135]

Maximum amplitude, mean, and standard deviation of EMG signals at biceps brachii muscles were strategically quantified, and they were larger for ALS patients compared to HC subjects.[136] Stockwell transform was applied to the EMG signal to extract features such as energy, mean, and standard deviation for the detection and classification of healthy and neuropathy.[137] Skewness and kurtosis of EEG spectra were utilized to detect mild cognitive impairment.[138]

Nonlinear features. Nonlinear dynamic features such as correlation dimension, Largest Lyapunov exponent, Hurst exponent, Lemplel–Ziv complexity, approximate entropy, and sample entropy extracted from the time series of the gait signals were explored for the diagnosis of PD.[139] The time series of multiple gait fluctuations can be embedded into the phase space, and then the topological signatures of barcodes were extracted by persistent homology.[140] Multifractal detrended cross-correlation analysis was also applied to study the autocorrelation and cross-correlation of the vGRF for both feet. It found that the multifractality and degree of correlation are generally more for HC than the NDDs.[141] For speech signal, the fractal jitter that explores the self-similarity of the variations in the fundamental frequency, as well as the multivariate fractal scaling exponent was extracted for better diagnosis of ALS.[142]

Entropy measures the uncertainty and randomness of the system. Multiscale approximate entropy was calculated from the vGRF of both feet to the diagnosis and long-term assessment of NDDs.[143] Sample entropy was determined for the stride time, with vector length and threshold parameters optimized PD, and it found that PD patients had higher sample entropy stride time than older adults, indicating reduced gait regularity.[144] Sigmoid entropy of EEG signal was found to be better and computationally efficient when compared to other entropy methods.[145] Shannon wavelet entropy, Renyyi wavelet entropy, Tsallis wavelet entropy, permutation entropy, and fuzzy entropy of both IMU and speech data can detect PD as well as their severity level.[146] Shannon entropy, permutation entropy, dispersion entropy, fluctuation-based dispersion entropy, slope entropy, bubble entropy, increment entropy, and bispectral entropy were extracted from the EEG signal for the PD diagnosis.[147]

The amount of divergence between the left and right stride, swing, and stance intervals was quantified by the dynamic gait series warping, Euclidean, Manhattan, Minkowski, Chebyshev, Canberra distances, and cosine function.[148] Hidden Markov models were used to encode
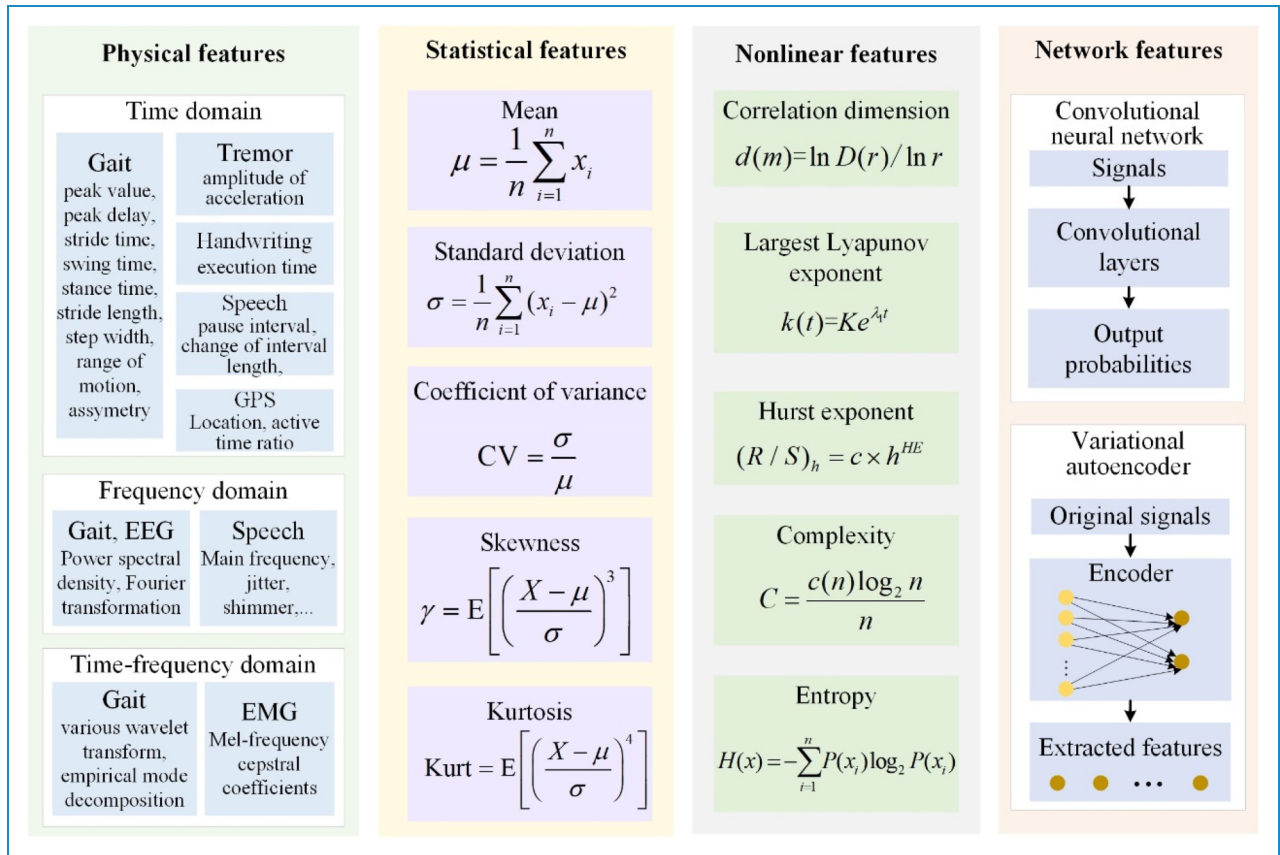
Figure 4. Various features applied to the detection of neurodegenerative diseases (NDDs).

the IMU gait sequences to extract their dynamics and provide a fixed-length representation.[149]

To create meaningful quantitative descriptions of behavioral characteristics of cerebellar ataxias, data collected from inertial sensors were analyzed by autoregressive hidden Markov models complied with a time-frequency approach.[150] Furthermore, a bag-of-words feature engineering method was developed: dividing each time series into subsequences, similar patterns are identified and a vocabulary was generated using the identified patterns. Then, word features were calculated based on the similarity of each subsequence to the vocabulary patterns. It outperforms the epoch-based statistical feature engineering method in the diagnosis of PD.[151]

Features extracted from networks. Features also can be extracted from networks. A deep convolutional neural network, referred to as a gait segmentation network had been developed and trained with the purpose of improving traditional gait segmentation from IMU at the fifth lumbar vertebrae and the ankles.[152]

Sets of vocal (speech) features were passed to the parallel input layers which are directly connected to convolutional layers, and deep features from each parallel branch were extracted simultaneously before combining in the merged layer.[153]

The latent factors of EEG were extracted by variational auto-encoders, and they can be mapped to the three-dimensional state space, thus the transient rotation of a neural state, which indicates the dynamic characteristics of latent factors can be found.[154]

Features selection

The extracted features may be redundant and some irrelevant features may overfit the diagnosing model as the sample size is limited. Thus, features selection processes have been designed to select discriminative features or discard redundant ones. Generally, depending on the relation to the latter diagnosing method, feature selection strategies can be divided into filter methods, wrapper methods, and embedded methods[155] as displayed in Figure 5.

Filter methods. Filter methods are independent of the classification process. They are effective in computation and robust to overfitting but key features may be missed. Moreover, they can provide interpretable and direct indications of disease influence.

Relevance indices. A good feature should not correlate to other features already selected. The correlation coefficient is the simplest approach to measure their relevance. The Spearman correlation coefficient to select the optimal feature set was applied with a stepwise regression method for PD diagnosis.[156] Mutual information (MI) between each of the features and the class label was determined based on the dependence of the target feature. Features with higher MI were retained since the high MI value represented less randomness and a higher correlation between the feature and its class.[157] Fisher score which measures the relevance between each dimension of the feature vectors and their assigned class labels, as well as Relief which reveals the dependencies of features and class labels were employed to reduce the dimensionality of speech features for PD classification.[158] Correlation feature subset selection has higher accuracy than the information gain and gain ratio for the AD prediction.[159] ReliefF algorithm computed the feature importance weights to detect PD from voice recordings.[160] There were also many multivariate techniques in filter methods for biomedical feature selection,[161] for example, a consistency-based filter selects subsets of features based on the degree of consistency with the class.

Significant difference analysis. Significant difference analysis aids to find out the distinctive features, and they may be the most commonly used approach in feature ranking or selection for NDDs diagnosis. Parametric tests such as analysis of variance (ANOVA) or Student's *t*-test analyze the data which conform to the Gaussian distribution (normally distributed variables), while nonparametric tests such as the Kruskal-Wallis test and Mann–Whitney *U* test deal with data that do not obey the Gaussian distribution.

ANOVA with recursive reduction was used to improve the dimension reduction and it reduced the number of sensors from 16 to 2 for plantar FSR.[162] For longitudinal data, variances tend to increase with time and covariances decrease with increasing intervals in time. Thus, ANOVA is not proper since it assumes the measured outcome saves equal variances and covariances over time. Therefore, multivariate ANOVA models that treat repeated observations as a vector had been utilized to detect HD progression.[163]

Student's *t*-test was applied to features extracted from vGRF to recognize how significant each feature was in terms of differentiating PD and control subjects.[164] Independent *t*-tests were employed to examine the difference between PD and HC, moreover, Pearson's correlation between gait characteristics was also evaluated to see the independence and redundancy.[165]

Wilcoxon rank-sum test ($p < 0.01$) proved that the approximate entropy, normalized symbolic entropy, and signal turns count are significantly larger for PD patients than HC.[166] Mann–Whitney *U* test observed some gait alteration in PD patients.[132]

Principal component analysis (PCA). Features dimensionality will sometimes be reduced by PCA. The PCA was used for feature enhancement of the recurrence plots transformed from the time-domain vGRF data.[167] PCA was implemented to reduce the dimensionality and select the most appropriate features from eight parameters namely mean, standard deviation, variance, skewness, kurtosis, energy, entropy, and correlation of each seven-gait feature (left stride interval, right stride interval, left swing interval, right swing interval, left stance interval, right stance interval, and double support).[168] For gait classification of NDDs, PCA removed correlated features within each symmetric measure (being involved in more than one time series for feature extraction).[148] PCA reduced the dimension of handwriting features, and the most representative features were found related to surface EMG.[56] Moreover, it can identify the differences in gait (e.g. hip and knee kinematics) from PD patients to HC.[169]

Wrapper methods. Wrapper methods need a learning model to evaluate candidate subsets and provide feedback. They have high accuracy and can identify key features in the cost of high time complexity, low operating efficiency, and poor generalization ability. Wrapper approaches aim to enhance the performance of the specific diagnosing model. The sequential feature selection method was utilized to reduce the number of features such as multiscale sample entropy values combined with statistical values extracted from the differential transformation of the vGRF signal.[170]

Regression approaches select or remove features based on the output of predictors. Stepwise regression models were proved to have superior convergent validity than PCA.[171] Evolutionary algorithms were applied to feature selection for AD diagnosis.[172] A generic algorithm is also a wrapper method, and it also belongs to the evolutionary algorithms. The best feature was selected using a fitness function and delivered to the next generation by a crossover operator.[173] Genetic algorithms and a binary classifier (X-ROC) were used to select the best combinations of EEG features for PD diagnosis.[174] Multiple ranks with a majority vote-based relative aggregate scoring model were proposed to select key features for PD analysis.[175]

Embedded methods. Embedded methods perform feature selection and classification simultaneously since features were selected in the training process. They were divided into regularization-based embedded feature selection and tree-based embedded feature selection.[176] A new feature selection method was developed by embedding the relational information inherent in the observations (sample–sample relation, feature–feature relation, and response–
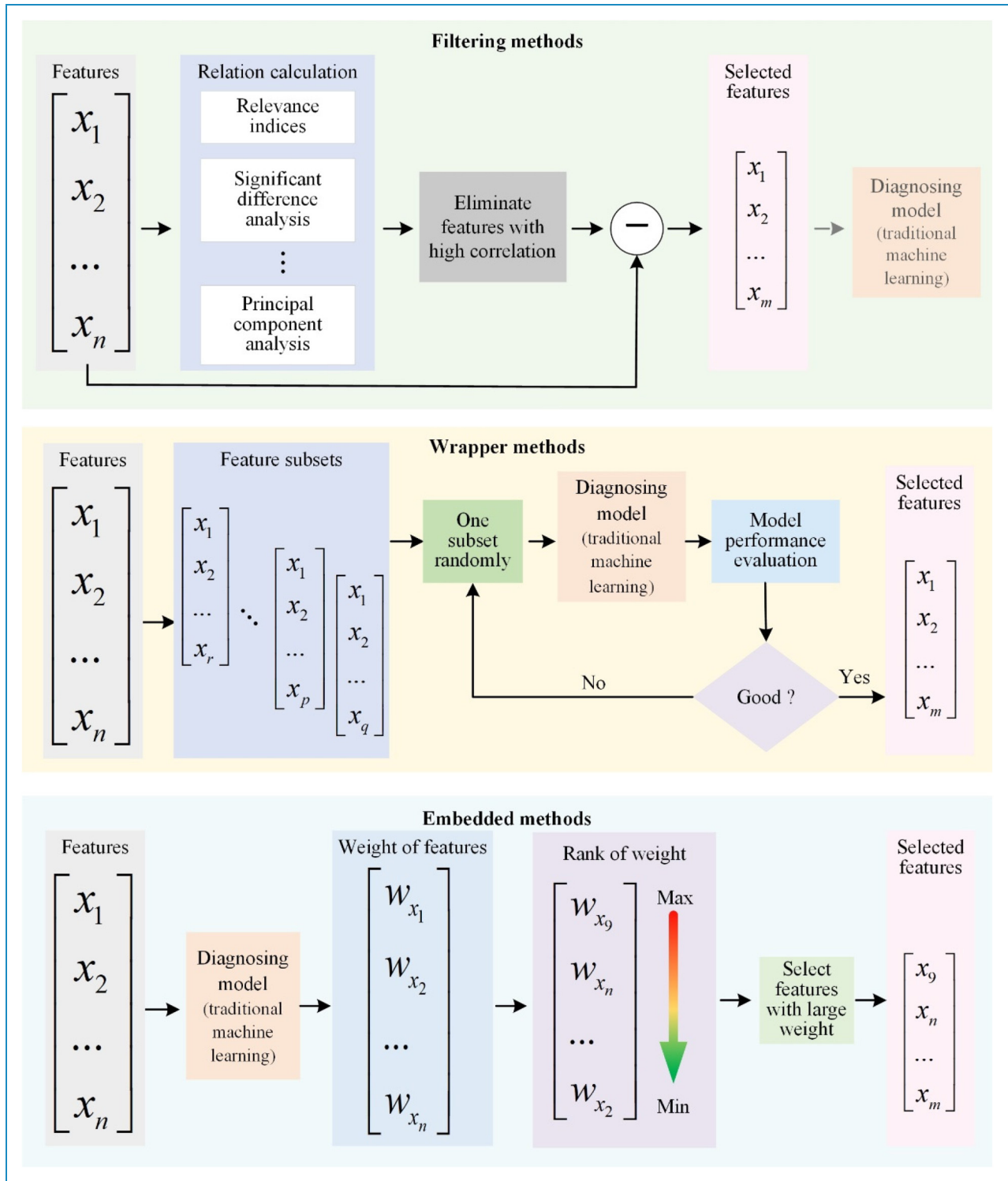
Figure 5. Feature selection methods utilized for the diagnosis of neurodegenerative diseases (NDDs).

response relation) into a sparse multi-task learning framework for the diagnosis of AD diagnosis.[177] A joint kernel-based feature selection approach was proposed to best benefit the classification scheme in the kernel space for the early diagnosis of PD.[178]

Hybrid method. There was no universal feature selection and classification method for medical datasets, different feature selection methods combined with different classification methods had been tried to find the best performance.[179] The mentioned three feature selection methods

were tested by speech features, ANOVA as filter method, sequential feature selection as wrapper method, least absolute shrinkage, and selection operator act as an embedded method, and both of them selected the jitter and shimmer.[180]

Wrapper methods combined with the filter method, such as Fisher's score and recursive feature elimination methods.[181] Pearson correlation coefficient and ReliefF were both applied to calculate the feature weight and then inputted into the discrete artificial bee colony algorithm for PD diagnosis.[182] Correlated feature selection combined with particle velocity clamping swarm optimization takes advantage of both the filters and the wrappers.[183] A hybrid MI gain and recursive feature elimination method selected 40 features out of 754 speech features, and it achieves the highest accuracy in classification than other standard feature selection approaches.[184] Features selected by filter and embedded methods were inputted to a wrapper-based approach optimizing both stability and predictability for AD prediction.[185]

Discussions

Applications for diagnosis

Feature extraction and selection aim to find distinctive features and they help an interpretable diagnosis of NDDs since most machine learning methods are limited by congenital observations. As mentioned, feature values of different NDDs were separated, and these discrepancies can be utilized as prior knowledge for the early diagnosis of corresponding NDD.[186] Machine learning based on handwritten, voice, and gait datasets was utilized for the diagnosis of PD in clinical decision-making.[187] Separate multivariable linear regression models and proportional odd regression models were applied to evaluate the relation of the Kinect measures to UPDRS motor and postural instability and gait difficulty scores.[188] Moreover, bradykinesia severity was measured by the frequency content of strides from a waist-worn sensor based on UPDRS scores estimated by support vector regression model.[189] Decision tree, random forest, K-nearest neighbor, Naïve Bayes, and support vector machine (SVM) were widely applied to various data for NDDs classification based on features.[123] SVM can produce efficient classification accuracy when feed directly with the features extracted by the wavelet transformation from the vGRF signals.[190] SVM was also the most used classification algorithm for the detection of AD, PD, HD, and ALS, respectively.[123] However, there are still challenges in the current applications of traditional machine learning in the diagnosis of NDDs domain. It is of great importance to properly address these issues in facilitating the clinical diagnosis and treatment strategy with the wearable system.

Influences of data collection

Sensors used in health monitoring and diagnosis that have reached an industrial level or that are at least at the stage of advanced field trials have been reviewed. Although the majority of works reported are not clinically and extensively validated for effectiveness confirmation, wearable sensors still present a promising impact on the diagnosis and monitoring of NDDs. On one hand, wearable sensors can achieve high accuracy when compared with videos of routine exercises, and the results show that sensor data analysis has the highest $f1$-score while handwriting is the most convenient.[191] On the other hand, the evaluation of PD developed from the in-lab devices such as force plate and needle EMG transitioned to wearable accelerometers/gyroscopes, and finally to phone and mobile applications in home monitoring.[192]

Evaluation of the health state or diagnosis of NDDs does not rely only on a single index or measurement even for clinic experts. Therefore, the wearable system should have the ability to collect different types of signals for more symptoms. With the rapid development of the smartphone, some sensors integrated into the phone and smart watches can collect versatile data such as speech signals, inertial signals, location data, and so on. In addition, the relationship of the signal obtained by the multisource sensors should be explored in the future. It is also worth noting that various tasks during data collection display different even contrastive effects on NDDs diagnosis. Self-selected walking speed conditions without dual tasking perform better for prodromal PD detection.[119] While some studies state that gait abnormalities were evident in dual cognitive tasks for PD patients.[193] To figure out the inherent influence of task effects on NDDs diagnosis, collecting more wearable data with more different tasks will be desired.

Challenges and prospects

This review will facilitate the research of wearable sensors as a noninvasive, less expensive, and potentially portable technique for NDDs' study, assessment, and diagnosis, particularly for low- and middle-income countries, which lack access to costly neuroimaging equipment. But there are still some challenges: (1) For wearable sensors, there remain considerable variability and lack of standardization in the wearable sensor technology platforms, type of clinometric data acquired, and remote monitoring resolution as it relates to the sensor location.[194] Using wearable sensors for the diagnosis of NDD is still in the exploration stage. Therefore, there are some limitations of existing research in the future clinical applications for the diagnosis of NDDs. The long-term test of the wearable sensors applications to patients has not been conducted for most of these wearable sensors. This is mainly limited by the personal

privacy of users, moreover, the long-term and low-burden ability of the power supply. (2) As for feature extraction and feature selection for diagnosis, most of the existing research mainly focuses on the analysis of signals based on the public dataset to find out the significant features and diagnosis method. The amount of public data collected from the wearable sensors is rare and thus lacks individual diversity, this lead to the mined information being limited and lack of generality. To deal with this issue, more data collected from wearable sensors are required and to be published in the future. (3) For the used dataset itself, most of the studies are cross-sectional studies, the NDDs and HC samples are independent even for some NDDs severity level studies, and the individual differences between each subject may submerge the alteration induced by the NDDs and their progression. Therefore, studying the NDDs progression with the longitudinal study will be helpful though it is challenging. (4) The summarized feature extraction and feature selection methods are fundamental procedures for diagnosis with the traditional machine learning method. With the development of deep learning methods, they have been introduced to the diagnosis of NDDs despite the lack of interpretability and transparency. Corresponding application and development in the diagnosis of NDDs should also be summarized in the future. In summary, to overcome these issues and develop an entire wearable system with NDDs diagnosis method based on machine learning in a complex space such as daily life, more longitudinal studies, and more cross-disciplinary training projects are needed. In addition, a collaboration between experts in biomedicine and machine learning is required.

Conclusions

This study provides a comprehensive examination of wearable sensors and features for the diagnosis of NDDs. The study includes 171 articles that were chosen after a thorough screening process. Crucial aspects of NDDs diagnosis were grouped under three main categories: wearable sensors, feature extraction, and feature selection. Such aspects have been reviewed, compared, and discussed, with the final goal of providing an overview of the state-of-the-art on wearable sensors for NDDs diagnosis and assessment. The application details such as principle, applied position, detecting events, strengths and drawbacks of force sensors, inertial sensors, EMG, EEG, acoustic sensors, optical fiber sensors, and GPSs have been illustrated and compared. Based on the wearable data, physical features, statistical features, nonlinear features, and features from the network have been illustrated and their alteration toward diseases have been displayed. Among these extracted features, feature selection methods including filtering, wrapper, and embedded methods have been illustrated to select discriminative features and achieve an efficient diagnosis. This review provides researchers with a complete view of the use of wearable sensors, feature extraction, and feature selection in NDDs diagnosis and monitoring. In the future, the wearable system can quantificationally evaluate the health state with interpretable results and records to help determine the need for medication changes in telemedicine applications further.

ORCID iD: Huan Zhao 🆔 https://orcid.org/0000-0001-6824-1570

References

1. Hou Y, Dan X, Babbar M, et al. Ageing as a risk factor for neurodegenerative disease. *Nat Rev Neurol* 2019; 15: 565–581.
2. Dugger BN and Dickson DW. Pathology of neurodegenerative diseases. *Cold Spring Harb Perspect Biol* 2017; 9: a28035.
3. Erkkinen MG, Kim MO and Geschwind MD. Clinical neurology and epidemiology of the major neurodegenerative diseases. *Cold Spring Harb Perspect Biol* 2018; 10: a033118.

4. Higuma M, Sanjo N, Mitoma H, et al. Whole-day gait monitoring in patients with Alzheimer's disease: A relationship between attention and gait cycle. *J Alzheimer's Dis Rep* 2017; 1: 1–8.

5. Zanardi APJ, Da Silva ES, Costa RR, et al. Gait parameters of Parkinson's disease compared with healthy controls: A systematic review and meta-analysis. *Sci Rep* 2021; 11: 752.

6. Shibasaki H, Tsuji S and Kuroiwa Y. Oculomotor abnormalities in Parkinson's disease. *Arch Neurol* 1979; 36: 360–364.

7. Chee JN, Ye B, Gregor S, et al. Influence of multiple sclerosis on spatiotemporal gait parameters: A systematic review and meta-regression. *Arch Phys Med Rehab* 2021; 102: 1801–1815.

8. Hausdorff JM, Lertratanakul A, Cudkowicz ME, et al. Dynamic markers of altered gait rhythm in amyotrophic lateral sclerosis. *J Appl Physiol* 2000; 88: 2045–2053.

9. Pyo SJ, Kim H, Kim IS, et al. Quantitative gait analysis in patients with Huntington's disease. *J Mov Disord* 2017; 10: 140–144.

10. Baquero M. Depressive symptoms in neurodegenerative diseases. *World J Clin Cases* 2015; 3: 82.

11. Cicirelli G, Impedovo D, Dentamaro V, et al. Human gait analysis in neurodegenerative diseases: A review. *IEEE J Biomed Health* 2022; 26: 229–242.

12. Myszczynska MA, Ojamies PN, Lacoste AMB, et al. Applications of machine learning to diagnosis and treatment of neurodegenerative diseases. *Nat Rev Neurol* 2020; 16: 440–456.

13. Salari N, Kazeminia M, Sagha H, et al. The performance of various machine learning methods for Parkinson's disease recognition: A systematic review. *Curr Psychol* 2022: 1–24. https://doi.org/10.1007/s12144-022-02949-8

14. Balakrishnan A, Medikonda J, Namboothiri PK, et al. Role of wearable sensors with machine learning approaches in gait analysis for Parkinson's disease assessment: A review. *Eng Sci* 2022; 19: 5–19.

15. Monje MHG, Foffani G, Obeso J, et al. New sensor and wearable technologies to aid in the diagnosis and treatment monitoring of Parkinson's disease. *Annu Rev Biomed Eng* 2019; 21: 111–143.

16. Lim ACY, Natarajan P, Fonseka RD, et al. The application of artificial intelligence and custom algorithms with inertial wearable devices for gait analysis and detection of gait-altering pathologies in adults: A scoping review of literature. *Digit Health* 2022; 8: 2012837451.

17. Barman J, Tirkey A, Batra S, et al. The role of nanotechnology based wearable electronic textiles in biomedical and healthcare applications. *Mater Today Commun* 2022; 32: 104055.

18. Nan X, Wang X, Kang T, et al. Review of flexible wearable sensor devices for biomedical application. *Micromachines* 2022; 13: 1395.

19. Mukherjee S, Suleman S, Pilloton R, et al. State of the art in smart portable, wearable, ingestible and implantable devices for health status monitoring and disease management. *Sensors* 2022; 22: 4228.

20. Albán-Cadena AC, Villalba-Meneses F, Pila-Varela KO, et al. Wearable sensors in the diagnosis and study of Parkinson's disease symptoms: A systematic review. *J Med Eng Technol* 2021; 45: 532–545.

21. Rovini E, Maremmani C and Cavallo F. How wearable sensors can support Parkinson's disease diagnosis and treatment: A systematic review. *Front Neurosci* 2017; 11: 555.

22. De Stefano C, Fontanella F, Impedovo D, et al. Handwriting analysis to support neurodegenerative diseases diagnosis: a review. *Pattern Recogn Lett* 2019; 121: 37–45.

23. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Int J Surg* 2021; 88: 105906.

24. Guk K, Han G, Lim J, et al. Evolution of wearable devices with real-time disease monitoring for personalized healthcare. *Nanomaterials* 2019; 9: 13.

25. Almuteb I, Hua R and Wang Y. Smart insoles review (2008–2021): Applications, potentials, and future. *Smart Health* 2022; 25: 100301.

26. Li W, Lu W, Sha X, et al. Wearable gait recognition systems based on MEMS pressure and inertial sensors: A review. *IEEE Sens J* 2022; 22: 1092–1104.

27. Faisal AI, Majumder S, Mondal T, et al. Monitoring methods of human body joints: State-of-the-art and research challenges. *Sensors* 2019; 19: 2629.

28. Celik Y, Stuart S, Woo WL, et al. Gait analysis in neurological populations: progression in the use of wearables. *Med Eng Phys* 2021; 87: 9–29.

29. Shen Z, Liu F, Huang S, et al. Progress of flexible strain sensors for physiological signal monitoring. *Biosens Bioelectron* 2022; 211: 114298.

30. Sundar A, Das C and Deshmukh MK. Novel applications of force sensing resistors in healthcare technologies. In: *Proceedings of healthy world conference*, Kolkata, India, 5–7 September 2015.

31. Grandez K, Bustamante P and Solas G. Neurodegenerative disease monitoring using a portable wireless sensor device [Internet]. In: Chang RC-C (ed) *Neurodegenerative diseases - processes, prevention, protection and monitoring*, 09 December 2011, London: InTech, pp.541–558. ISBN: 9533074856 9789533074856.

32. Setiawan F and Lin C. Identification of neurodegenerative diseases based on vertical ground reaction force classification using time–frequency spectrogram and deep learning neural network features. *Brain Sci* 2021; 11: 2.

33. Selzler R, Green JR and Goubran R. Neurodegenerative disease prediction based on gait analysis signals acquired with force-sensitive resistors. In: *2018 IEEE life sciences conference (LSC)*, Montreal, QC, Canada, 28–30 October 2018, pp.122–125. New York: IEEE.

34. Homayounfar SZ and Andrew TL. Wearable sensors for monitoring human motion: A review on mechanisms, materials, and challenges. *SLAS Technol* 2020; 25: 9–24.

35. Goldberger AL, Amaral LA, Glass L, et al. Physiobank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. *Circulation* 2000; 101: E215–E220.

36. Xu Q, Gao X, Zhao S, et al. Construction of bio-piezoelectric platforms from structures and synthesis to applications. *Adv Mater* 2021; 27: 2008452.

37. Wang Y, Yu Y, Wei X, et al. Self-powered wearable piezoelectric monitoring of human motion and physiological

signals for the postpandemic era: A review. *Adv Mater Technol* 2022; 7: 2200318.

38. Liu D, Zhang D, Sun Z, et al. Active-matrix sensing array assisted with machine-learning approach for lumbar. *Adv Funct Mater* 2022; 21: 2113008.

39. Zhao H, Wang R, Qi D, et al. Wearable gait monitoring for diagnosis of neurodegenerative diseases. *Measurement* 2022; 202: 111839.

40. Zhang Z, Xu Z, Chen W, et al. Comparison between piezo-electric and piezoresistive wearable gait monitoring techniques. *Materials* 2022; 15: 4837.

41. Ullah H, Wahab MA, Will G, et al. Recent advances in stretchable and wearable capacitive electrophysiological sensors for long-term health monitoring. *Biosensors* 2022; 12: 30.

42. Sakthivelpathi V, Qian Z, Li T, et al. Capacitive eye tracker made of fractured carbon nanotube-paper composites for wearable applications. *Sens Actuators A* 2022; 344: 113739.

43. Mathew AA, Chandrasekhar A and Vivekanandan S. A review on real-time implantable and wearable health monitoring sensors based on triboelectric nanogenerator approach. *Nano Energy* 2021; 80: 105566.

44. Buckley C, Alcock L, McArdle R, et al. The role of movement analysis in diagnosing and monitoring neurodegenerative conditions: Insights from gait and postural control. *Brain Sci* 2019; 9: 34.

45. Louter M, Maetzler W, Prinzen J, et al. Accelerometer-based quantitative analysis of axial nocturnal movements differentiates patients with Parkinson's disease, but not high-risk individuals, from controls. *J Neurol Neurosurg Psychiatry* 2014; 86: 32–37.

46. Maetzler W, Mancini M, Liepelt-Scarfone I, et al. Impaired trunk stability in individuals at high risk for Parkinson's disease. *PLoS One* 2012; 7: e32240.

47. Montero-Odasso M, Pieruccini-Faria F, Bartha R, et al. Motor phenotype in neurodegenerative disorders: Gait and balance platform study design protocol for the Ontario Neurodegenerative Research Initiative (ONDRI). *J Alzheimer's Dis* 2017; 59: 707–721.

48. Dasgupta P, VanSwearingen J, Godfrey A, et al. Acceleration gait measures as proxies for motor skill of walking: A narrative review. *IEEE Trans Neural Syst Rehabil Eng* 2021; 29: 249–261.

49. Srulijes K, Klenk J, Schwenk M, et al. Fall risk in relation to individual physical activity exposure in patients with different neurodegenerative diseases: A pilot study. *Cerebellum* 2019; 18: 340–348.

50. Gibson RM, Amira A, Ramzan N, et al. Matching pursuit-based compressive sensing in a wearable biomedical accelerometer fall diagnosis device. *Biomed Signal Proces* 2017; 33: 96–108.

51. Ali SH, Akhtar A, Khan MA, et al. Detection of Parkinson's tremor in real time using accelerometers. In: *2021 IEEE 7th international conference on smart instrumentation, measurement and applications (ICSIMA)*, Bandung, Indonesia, 23–25 August 2021, pp.5–9. New York: IEEE.

52. Jeng B, Cederberg KLJ, Lai B, et al. Wrist-based accelerometer cut-points for quantifying moderate-to-vigorous intensity physical activity in Parkinson's disease. *Gait Posture* 2022; 91: 235–239.

53. LeMoyne R, Mastroianni T, Cozza M, et al. Implementation of an iPhone for characterizing Parkinson's disease tremor through a wireless accelerometer application. In: *2010 annual international conference of the IEEE engineering in medicine and biology*, Buenos Aires, Argentina, 31 August – 04 September 2010, pp.4954–4958. New York: IEEE.

54. Balachandar A, Algarni M, Oliveira L, et al. Are smart-phones and machine learning enough to diagnose tremor? *J Neurol* 2022; 269: 6104–6115.

55. Donohue C, Khalifa Y, Perera S, et al. A preliminary investigation of whether HRCA signals can differentiate between swallows from healthy people and swallows from people with neurodegenerative diseases. *Dysphagia* 2021; 36: 635–643.

56. Loconsole C, Cascarano GD, Brunetti A, et al. A model-free technique based on computer vision and sEMG for classification in Parkinson's disease by using computer-assisted handwriting analysis. *Pattern Recogn Lett* 2019; 121: 28–36.

57. Gugliandolo G, Campobello G, Capra PP, et al. A movement-tremors recorder for patients of neurodegenerative diseases. *IEEE Trans Instrum Meas* 2019; 68: 1451–1457.

58. Elble RJ and McNames J. Using portable transducers to measure tremor severity. *Tremor Other Hyperkinet Mov (NY)* 2016; 6: 375.

59. Duque JDL, Egea AJS, Reeb T, et al. Angular velocity analysis boosted by machine learning for helping in the differential diagnosis of Parkinson's disease and essential tremor. *IEEE Access* 2020; 8: 88866–88875.

60. Navya JS, Rajasree S and Ullas B. Non-invasive fall detection system for Parkinson's disease. In: *2018 International CET conference on control, communication, and computing (IC4)*, Thiruvananthapuram, India, 5–7 July 2018, pp.157–160. New York: IEEE.

61. Tiwari S, Sharma V, Mujawar M, et al. Biosensors for epilepsy management: state-of-art and future aspects. *Sensors* 2019; 19: 1525.

62. Talitckii A, Anikina A, Kovalenko E, et al. Defining optimal exercises for efficient detection of Parkinson's disease using machine learning and wearable sensors. *IEEE Trans Instrum Meas* 2021; 70: 1–10.

63. Ligorio G, Bergamini E, Truppa L, et al. A wearable magnetometer-free motion capture system: innovative solutions for real-world applications. *IEEE Sens J* 2020; 20: 8844–8857.

64. Iosa M, Picerno P, Paolucci S, et al. Wearable inertial sensors for human movement analysis. *Expert Rev Med Devices* 2016; 7: 641–659.

65. Picerno P, Iosa M, D'Souza C, et al. Wearable inertial sensors for human movement analysis: a five-year update. *Expert Rev Med Devices* 2021; 18: 79–94.

66. Perez-Jimenez MA, Martinez-Castillo J, Morales-Gonzalez E, et al. A portable and wireless system for monitoring hand tremors in Parkinson's disease patients. In: *2019 IEEE international conference on engineering Veracruz (ICEV)*, Boca del Rio, Mexico, 14–17 October 2019, pp.1–4. New York: IEEE.

67. Caramia C, Torricelli D, Schmid M, et al. IMU-based classification of Parkinson's disease from gait: A sensitivity analysis on sensor location and feature selection. *IEEE J Biomed Health* 2018; 22: 1765–1774.

68. Pierleoni P, Raggiunto S, Belli A, et al. A single wearable sensor for gait analysis in Parkinson's disease: A preliminary study. *Appl Sci* 2022; 12: 5486.

69. Lukšys D, Jatužis D, Jonaitis G, et al. Application of continuous relative phase analysis for differentiation of gait in neurodegenerative disease. *Biomed Signal Process* 2021; 67: 102558.

70. Avalle M, Belotti V, Frascio M, et al. Development of a wearable device for the early diagnosis of neurodegenerative diseases. *IOP Conf Ser Mater Sci Eng* 2021; 1038: 12033.

71. Zhang H, Deng K, Li H, et al. Deep learning identifies digital biomarkers for self-reported Parkinson's disease. *Patterns* 2020; 1: 100042.

72. Juutinen M, Wang C, Zhu J, et al. Parkinson's disease detection from 20-step walking tests using inertial sensors of a smartphone: Machine learning approach based on an observational case-control study. *PLoS One* 2020; 15: e236258.

73. Ibrahim AFT, Gannapathy VR, Chong LW, et al. Analysis of electromyography (EMG) signal for human arm muscle: A Review. In: Sulaiman H, Othman M, Othman M, et al. (eds) *Advanced Computer and Communication Engineering Technology*. Lecture Notes in Electrical Engineering, vol 362. Cham: Springer, 2016, pp.567–575. https://doi.org/10.1007/978-3-319-24584-3_49

74. Bashford J, Mills K and Shaw C. The evolving role of surface electromyography in amyotrophic lateral sclerosis: A systematic review. *Clin Neurophysiol* 2020; 131: 942–950.

75. Sushkova OS, Morozov AA, Gabova AV, et al. Investigation of phase analysis methods of antagonist muscles electromyograms in patients with neurodegenerative diseases. In: *2021 international conference on information technology and nanotechnology (ITNT)*, Samara, Russian Federation, 20–24 September 2021, pp.1–5. New York: IEEE.

76. Fricke C, Alizadeh J, Zakhary N, et al. Evaluation of three machine learning algorithms for the automatic classification of EMG patterns in gait disorders. *Front Neurol* 2021: 12: 666458.

77. Rezaee K, Savarkar S, Yu X, et al. A hybrid deep transfer learning-based approach for Parkinson's disease classification in surface electromyography signals. *Biomed Signal Process* 2022; 71: 103161.

78. Adem HM, Tessema AW and Simegn GL. Classification of Parkinson's disease using EMG signals from different upper limb movements based on multiclass support vector machine. *Int J Bioautomation* 2022; 26: 109–125.

79. Nishikawa Y, Holobar A, Watanabe K, et al. Detecting motor unit abnormalities in amyotrophic lateral sclerosis using high-density surface EMG. *Clin Neurophysiol* 2022; 142: 262–272.

80. Kleinholdermann U, Wullstein M and Pedrosa D. Prediction of motor unified Parkinson's disease rating scale scores in patients with Parkinson's disease using surface electromyography. *Clin Neurophysiol* 2021; 132: 1708–1713.

81. Liu Y, Zhang J, Lam SP, et al. Electromyography activity level in rapid eye movement sleep predicts neurodegenerative diseases in idiopathic rapid eye movement sleep behavior disorder: A 5-year longitudinal study. *Sleep Med* 2019; 56: 128–134.

82. Dede HÖ, Benbir Senel G and Karadeniz D. Rapid eye movement sleep without atonia constitutes increased risk for neurodegenerative disorders. *Acta Neurol Scand* 2019; 140: 399–404.

83. McMackin R, Muthuraman M, Groppa S, et al. Measuring network disruption in neurodegenerative diseases: New approaches using signal analysis. *J Neurol Neurosurg Psychiatry* 2019; 90: 1011–1020.

84. Muñoz D, Barria P, Cifuentes CA, et al. EEG Evaluation in a neuropsychological intervention program based on virtual reality in adults with Parkinson's disease. *Biosensors* 2022; 12: 51.

85. Cassani R, Estarellas M, San-Martin R, et al. Systematic review on resting-state EEG for Alzheimer's disease diagnosis and progression assessment. *Dis Markers* 2018; 2018: 1–26.

86. Cassani R, Falk TH, Fraga FJ, et al. Towards automated electroencephalography-based Alzheimer's disease diagnosis using portable low-density devices. *Biomed Signal Process* 2017; 33: 261–271.

87. Mihajlovic V, Grundlehner B, Vullers R, et al. Wearable, wireless EEG solutions in daily life applications: what are we missing? *IEEE J Biomed Health Inform* 2015; 19: 6–21.

88. Rockhill AP, Jackson N, George J, et al. *UC San Diego resting state EEG data from patients with Parkinson's disease. Technical Report.* University of California, San Diego, CA, USA, 2020.

89. Cavanagh JF, Kumar P, Mueller AA, et al. Diminished EEG habituation to novel events effectively classifies Parkinson's patients. *Clin Neurophysiol* 2018; 129: 409–418.

90. Cecchi M, Moore DK, Sadowsky CH, et al. A clinical trial to validate event-related potential markers of Alzheimer's disease in outpatient settings. *Alzheimers Dement* 2015; 1: 387–394.

91. McGovern K. Acoustic intensity and speech breathing kinematics in a patient with Parkinson's disease, University of Pittsburgh, 2018.

92. Perez M, Jin W, Le D, et al. Classification of Huntington disease using acoustic and Lexical Features. *Interspeech* 2018; 2018: 1898–1902.

93. Vizza P, Tradigo G, Mirarchi D, et al. Methodologies of speech analysis for neurodegenerative diseases evaluation. *Int J Med Inform* 2019; 122: 45–54.

94. Gugliandolo G, Campobello G, Marinkovic Z, et al. Development of a multi-transduction system for breath analysis in neurodegenerative diseases. In: *2021 IEEE international symposium on medical measurements and applications (MeMeA)*, Lausanne, Switzerland, 23–25 June 2021, pp.1–6. New York: IEEE.

95. Wang J, Kothalkar PV, Cao B, et al. Towards automatic detection of amyotrophic lateral sclerosis from speech acoustic and articulatory samples, In: *17th Annual conference of the international speech communication association (INTERSPEECH 2016)*, 8–12 September 2016. San Francisco, USA: René CARRÉ: International Speech Communication Association (ISCA).

96. Zhang H, Song C, Wang A, et al. PDVocal: Towards privacy-preserving Parkinson's disease detection using non-

speech body sounds. In: *The 25th annual international conference on mobile computing and networking*, Los Cabos, Mexico, August 2019, pp.1–16. New York: Association for Computing Machinery.

97. Rusz J, Hlavnicka J, Tykalova T, et al. Smartphone allows capture of speech abnormalities associated with high risk of developing Parkinson's disease. *IEEE Trans Neural Syst Rehabil Eng* 2018; 26: 1495–1507.

98. Singh J, Rajnish R and Singh DK. Designing a machine learning model to predict Parkinson's disease from voice recordings. In: *Second international conference on sustainable technologies for computational intelligence*, Dehradun, India, 22–23 May 2021, pp.95–103. New York: Springer.

99. Mamun KAA, Alhussein M, Sailunaz K, et al. Cloud based framework for Parkinson's disease diagnosis and monitoring system for remote healthcare applications. *Future Gener Comput Syst* 2017; 66: 36–47.

100. Sakar BE, Isenkul ME, Sakar CO, et al. Collection and analysis of a Parkinson speech dataset with multiple types of sound recordings. *IEEE J Biomed Health* 2013; 17: 828–834.

101. Dua D and Karra Taniskidou E. *UCI machine learning repository*. Available at: http://archive.ics.uci.edu/ml (accessed 6 May 2023).

102. F. Boller, J. Becker, *Dementia-bank database guide*. University of Pittsburgh, 2005.

103. Li F, Stewart C, Yang S, et al. Optical sensor array for the early diagnosis of Alzheimer's disease. *Front Chem* 2022: 10: 874864.

104. Stupar DZ, Bajic JS, Manojlovic LM, et al. Wearable low-cost system for human joint movements monitoring based on fiber-optic curvature sensor. *IEEE Sens J* 2012; 12: 3424–3431.

105. Guo J, Zhou B, Zong R, et al. Stretchable and highly sensitive optical strain sensors for human-activity monitoring and healthcare. *ACS Appl Mater Int* 2019; 11: 33589–33598.

106. Zhu X, Liu W, Shuang S, et al. Intelligent tattoos, patches, and other wearable biosensors. In: Narayan RJ (ed): *Medical biosensors for point of care (POC) applications*. Cambridge: Woodhead Publishing, 2017, pp.133–150.

107. Domingues MF, Nepomuceno A, Tavares C, et al. Energy-aware wearable e-health architecture using optical FBG sensors for knee kinematic monitoring. In: *2018 IEEE global communications conference (GLOBECOM)*, Abu Dhabi, United Arab Emirates, 09–13 December 2018, pp. 1–6. New York: IEEE.

108. Domingues MF, Tavares C, Nepomuceno AC, et al. Non-invasive wearable optical sensors for full gait analysis in E-health architecture. *IEEE Wirel Commun* 2021; 28: 28–35.

109. Fillekes MP, Kim E, Trumpf R, et al. Assessing older adults' daily mobility: a comparison of GPS-derived and self-reported mobility indicators. *Sensors* 2019; 19: 4551.

110. Ó Breasail M, Biswas B, Smith M, et al. Wearable GPS and accelerometer technologies for monitoring mobility and physical activity in neurodegenerative disorders: A systematic review. *Sensors* 2021; 21: 8261.

111. Zhu L, Duval C, Boissy P, et al. Comparing GPS-based community mobility measures with self-report assessments in older adults with Parkinson's disease. *J Gerontol A Biol Sci Med Sci* 2020; 75: 2361–2370.

112. Tung JY, Rose RV, Gammada E, et al. Measuring life space in older adults with mild-to-moderate Alzheimer's disease using mobile phone GPS. *Gerontology* 2014; 60: 154–162.

113. Bayat S, Babulal GM, Schindler SE, et al. GPS driving: A digital biomarker for preclinical Alzheimer disease. *Alz Res Ther* 2021: 13: 115.

114. De Vos M, Prince J, Buchanan T, et al. Discriminating progressive supranuclear palsy from Parkinson's disease using wearable technology and machine learning. *Gait Posture* 2020; 77: 257–263.

115. Paul S, Saikia A, Hussain M, et al. EEG–EMG correlation for Parkinson's disease. *Int J Eng Adv Technol* 2019; 8: 1179–1185.

116. Virginia Anikwe C, Friday Nweke H, Chukwu Ikegwu A, et al. Mobile and wearable sensors for data-driven health monitoring system: State-of-the-art and future prospect. *Expert Syst Appl* 2022; 202: 117362.

117. Farashi S. Distinguishing between Parkinson's disease patients and healthy individuals using a comprehensive set of time, frequency and time-frequency features extracted from vertical ground reaction force data. *Biomed Signal Process* 2020; 62: 102132.

118. Balaji E, Brindha D, Elumalai VK, et al. Data-driven gait analysis for diagnosis and severity rating of Parkinson's disease. *Med Eng Phys* 2021; 91: 54–64.

119. Del DS, Elshehabi M, Galna B, et al. Gait analysis with wearables predicts conversion to Parkinson disease. *Ann Neurol* 2019; 86: 357–367.

120. Donisi L, Cesarelli G, Balbi P, et al. Positive impact of short-term gait rehabilitation in Parkinson patients: a combined approach based on statistics and machine learning. *Math Biosci Eng* 2021; 18: 6995–7009.

121. Salarian A, Russmann H, Wider C, et al. Quantification of tremor and bradykinesia in Parkinson's disease using a novel ambulatory monitoring system. *IEEE Trans Biomed Eng* 2007; 54: 313–322.

122. Loconsole C, Trotta GF, Brunetti A, et al. Computer vision and EMG-based handwriting analysis for classification in Parkinson's disease. In: *International conference on intelligent computing*, Liverpool, UK, 7–10 August 2017, pp 493–503. Cham: Springer.

123. Tăuţan A, Ionescu B and Santarnecchi E. Artificial intelligence in neurodegenerative diseases: A review of available tools with a focus on machine learning techniques. *Artif Intell Med* 2021; 117: 102081.

124. Das KD, Saji AJ and Kumar CS, Frequency analysis of gait signals for detection of neurodegenerative diseases. In: *2017 international conference on circuits power and computing technologies*, Kollam, India, 20–21 April 2017, pp.1–6. New York: IEEE.

125. Chua KC, Chandran V, Acharya UR, et al. Application of higher order statistics/spectra in biomedical signals—a review. *Med Eng Phys* 2010; 32: 679–689.

126. Durongbhan P, Zhao Y, Chen L, et al. A dementia classification framework using frequency and time-frequency features based on EEG signals. *IEEE Trans Neural Syst Rehabil Eng* 2019; 27: 826–835.

127. Bilgin S. The impact of feature extraction for the classification of amyotrophic lateral sclerosis among

neurodegenerative diseases and healthy subjects. *Biomed Signal Process* 2017; 31: 288–294.

128. Setiawan F, Liu A and Lin C. Development of neurodegenerative diseases' gait classification algorithm using convolutional neural network and wavelet coherence spectrogram of gait synchronization. *IEEE Access* 2022; 10: 38137–38153.

129. Zeng W, Yuan C, Wang Q, et al. Classification of gait patterns between patients with Parkinson's disease and healthy controls using phase space reconstruction (PSR), empirical mode decomposition (EMD) and neural networks. *Neural Netw* 2019; 111: 64–76.

130. Sushkova OS, Morozov AA, Gabova AV, et al. Investigation of surface EMG and acceleration signals of limbs' tremor in Parkinson's disease patients using the method of electrical activity analysis based on wave trains. In: *Ibero-American conference on artificial intelligence*, Trujillo, Peru, 13–16 November 2018, pp.253–264. Cham: Springer.

131. Sakar CO, Serbes G, Gunduz A, et al. A comparative analysis of speech signal processing algorithms for Parkinson's disease classification and the use of the tunable Q-factor wavelet transform. *Appl Soft Comput* 2019; 74: 255–263.

132. Zhao H, Cao J, Wang R, et al. Accurate identification of Parkinson's disease by distinctive features and ensemble decision trees. *Biomed Signal Process* 2021; 69: 102860.

133. Ferreira MIAS, Barbieri FA, Moreno VC, et al. Machine learning models for Parkinson's disease detection and stage classification based on spatial-temporal gait parameters. *Gait Posture* 2022; 98: 49–55.

134. Nóbrega LR, Cabral AM, Oliveira FHM, et al. Wrist movement variability assessment in individuals with Parkinson's disease. *Healthcare* 2022; 10: 1656.

135. Saljuqi M and Ghaderyan P. A novel method based on matching pursuit decomposition of gait signals for Parkinson's disease, Amyotrophic lateral sclerosis and Huntington's disease detection. *Neurosci Lett* 2021; 761: 136107.

136. Sengar N, Dutta MK and Travies CM. Identification of amyotrophic lateral sclerosis using EMG signals. In: *2017 4th IEEE Uttar Pradesh section international conference on electrical, computer and electronics (UPCON)*, Mathura, India, 26–28 October 2017, pp.468–471. New York: IEEE.

137. Roy SS, Jana R, Barman R, et al. Detection of healthy and neuropathy electromyograms employing Stockwell transform. In: *2018 IEEE applied signal processing conference (ASPCON)*, Kolkata, India, 07–09 December 2018, pp 214–218. New York: IEEE.

138. Sharma N, Kolekar MH, Jha K, et al. EEG and cognitive biomarkers based mild cognitive impairment diagnosis. *IRBM* 2019; 40: 113–121.

139. Carvajal-Castaño HA, Lemos-Duque JD and Orozco-Arroyave JR. Effective detection of abnormal gait patterns in Parkinson's disease patients using kinematics, nonlinear, and stability gait features. *Hum Movement Sci* 2022; 81: 102891.

140. Yan Y, Omisore OM, Xue Y, et al. Classification of neurodegenerative diseases via topological motion analysis—a comparison study for multiple gait fluctuations. *IEEE Access* 2020; 8: 96363–96377.

141. Dutta S, Ghosh D and Samanta S. Non linear approach to study the dynamics of neurodegenerative diseases by multifractal detrended cross-correlation analysis—a quantitative assessment on gait disease. *Physica A* 2016; 448: 181–195.

142. Spangler T, Vinodchandran NV, Samal A, et al. Fractal features for automatic detection of dysarthria. In: *2017 IEEE EMBS international conference on biomedical & health informatics (BHI), 13 April 2017*, Orlando, FL, USA, pp 437–440. New York: IEEE.

143. Liu A and Lin C. Multiscale approximate entropy for gait analysis in patients with neurodegenerative diseases. *Entropy* 2019; 21: 34.

144. Coates L, Shi J, Rochester L, et al. Entropy of real-world gait in Parkinson's disease determined from wearable sensors as a digital marker of altered ambulatory behavior. *Sensors* 2020; 20: 2631.

145. Raghu S, Sriraam N, Temel Y, et al. Performance evaluation of DWT based sigmoid entropy in time and frequency domains for automated detection of epileptic seizures using SVM classifier. *Comput Biol Med* 2019; 110: 127–143.

146. Oung QW, Muthusamy H, Basah SN, et al. Empirical wavelet transform based features for classification of Parkinson's disease severity. *J Med Syst* 2018: 42: 29.

147. Chawla P, Rana SB, Kaur H, et al. A decision support system for automated diagnosis of Parkinson's disease from EEG using FAWT and entropy features. *Biomed Signal Process* 2023; 79: 104116.

148. Ghaderyan P and Ghoreshi Beyrami SM. Neurodegenerative diseases detection using distance metrics and sparse coding: A new perspective on gait symmetric features. *Comput Biol Med* 2020; 120: 103736.

149. Cuzzolin F, Sapienza M, Esser P, et al. Metric learning for Parkinsonian identification from IMU gait measurements. *Gait Posture* 2017; 54: 127–132.

150. Knudson KC and Gupta AS. Assessing cerebellar disorders with wearable inertial sensor data using time-frequency and autoregressive hidden Markov model approaches. *Sensors* 2022; 22: 9454.

151. Rastegari E and Ali H. A bag-of-words feature engineering approach for assessing health conditions using accelerometer data. *Smart Health* 2020; 16: 100116.

152. Gadaleta M, Cisotto G, Rossi M, et al. Deep learning techniques for improving digital gait segmentation. *Annu Int Conf IEEE Eng Med Biol Soc* 2019; 2019: 1834–1837.

153. Gunduz H. Deep learning-based Parkinson's disease classification using vocal feature sets. *IEEE Access* 2019; 7: 115540–115551.

154. Li K, Wang J, Li S, et al. Feature extraction and identification of Alzheimer's disease based on latent factor of multi-channel EEG. *IEEE Trans Neural Syst Rehabil Eng* 2021; 29: 1557–1567.

155. Guyon I, Nikravesh M, Gunn S, et al. *Feature extraction foundations and applications*. Berlin: Springer, 2006.

156. Mehra N and Mittal P. Design and implementation of ML model for early diagnosis of Parkinson's disease using gait data analysis in IoT environment. *Int J Adv Comput Sci Appl* 2022: 13: 580–589. https://doi.org/10.14569/IJACSA.2022.0130769

157. Gupta K, Khajuria A, Chatterjee N, et al. Rule based classification of neurodegenerative diseases using data driven gait features. *Health Technol* 2019; 9: 547–560.

158. Gunduz H. An efficient dimensionality reduction method using filter-based feature selection and variational autoencoders on Parkinson's disease classification. *Biomed Signal Process* 2021; 66: 102452.

159. Tejeswinee K, Shomona GJ and Athilakshmi R. Feature selection techniques for prediction of neurodegenerative disorders: A case-study with Alzheimer's and Parkinson's disease. *Procedia Comput Sci* 2017; 115: 188–194.

160. Demir F, Siddique K, Alswaitti M, et al. A simple and effective approach based on a multi-level feature selection for automated Parkinson's disease detection. *J Pers Med* 2022; 12: 55.

161. Remeseiro B and Bolon-Canedo V. A review of feature selection methods in medical applications. *Comput Biol Med* 2019; 112: 103375.

162. Ma Y, Chen J, Chen Y, et al. Explainable deep learning architecture for early diagnosis of Parkinson's disease. *Soft Comput* 2023; 27: 2729–2738.

163. Garcia TP and Marder K. Statistical approaches to longitudinal data analysis in neurodegenerative diseases: Huntington's disease as a model. *Curr Neurol Neurosci* 2017; 17: 14.

164. Yurdakul OC, Subathra MSP and George ST. Detection of Parkinson's disease from gait using neighborhood representation local binary patterns. *Biomed Signal Proces* 2020; 62: 102070.

165. Rehman RZU, Del Din S, Guan Y, et al. Selecting clinically relevant gait characteristics for classification of early Parkinson's disease: A comprehensive machine learning approach. *Sci Rep* 2019; 9: Article number 17269.

166. Wu Y, Chen P, Luo X, et al. Measuring signal fluctuations in gait rhythm time series of patients with Parkinson's disease using entropy parameters. *Biomed Signal Process* 2017; 31: 265–271.

167. Lin C, Wen T and Setiawan F. Evaluation of vertical ground reaction forces pattern visualization in neurodegenerative diseases identification using deep learning and recurrence plot image feature extraction. *Sensors* 2020; 20: 3857.

168. Amin S and Singhal A. Identification and classification of neuro-degenerative diseases using feature selection through PCA-LD. In: *2017 4th IEEE Uttar Pradesh section international conference on electrical, computer and electronics (UPCON)*, Mathura, India, 26–28 October 2017, pp.578–586. New York: IEEE.

169. Luksys D, Jatuzis D, Kaladyte-Lokominiene R, et al. Differentiation of gait using principal component analysis and application for Parkinson's disease monitoring. In: *2018 international conference BIOMDLORE*, Bialystok, Poland, 28–430 June 2018, pp.1–4. New York: IEEE.

170. Nam Nguyen QD, Liu A and Lin C. Development of a neurodegenerative disease gait classification algorithm using multiscale sample entropy and machine learning classifiers. *Entropy* 2020; 22: 1340.

171. Aghanavesi S, Bergquist F, Nyholm D, et al. Motion sensor-based assessment of Parkinson's disease motor symptoms during leg agility tests: results from levodopa challenge. *IEEE J Biomed Health* 2020; 24: 111–119.

172. Gutierrez FG, Alvarez AD, Alonso CD, et al. Diagnosis of Alzheimer's disease and behavioural variant frontotemporal dementia with machinelearning-aided neuropsychological assessment using feature engineering and genetic algorithms. *Int J Geriatr Psychiatry* 2022; 37 :1–13. https://doi.org/10.1002/gps.5667

173. Srinivasa M and Koolagudi SG. Classification of vocal and non-vocal segments in audio clips using genetic algorithm based feature selection. *Expert Syst Appl* 2018; 106: 77–91.

174. Silva G, Alves M, Cunha R, et al. Parkinson disease early detection using EEG channels cross-correlation. *Int J Appl Eng Res* 2020; 15: 197–203.

175. Gopalsamy A and Radha B. Feature selection using multiple ranks with majority vote-based relative aggregate scoring model for Parkinson dataset. In: *Proceedings of international conference on data science and applications: ICDSA*, Kolkata, India, 10–11 April, 2021, pp.1–19. Singapore: Springer.

176. Mahendran N and Durai Raj Vincent PM. A deep learning framework with an embedded-based feature selection approach for the early detection of the Alzheimer's disease. *Comput Biol Med* 2022; 141: 105056.

177. Zhu X, Suk H, Wang L, et al. A novel relational regularization feature selection method for joint regression and classification in AD diagnosis. *Med Image Anal* 2017; 38: 205–214.

178. Adeli E, Wu G, Saghafi B, et al. Kernel-based joint feature selection and max-margin classification for early diagnosis of Parkinson's disease. *Sci Rep* 2017; 7: 41069.

179. Lamba R, Gulati T, Alharbi HF, et al. A hybrid system for Parkinson's disease diagnosis using machine learning techniques. *Int J Speech Technol* 2022; 3: 583–593.

180. Avijit Kumar Dash. Prediction of Parkinson's disease using hybrid feature selection based techniques. In: *4th international conference on computing and communications technologies (ICCCT)*, Chennai, India, 18 February 2022, pp.46–51. New York: IEEE.

181. Valla E, Nõmm S, Medijainen K, et al. Tremor-related feature engineering for machine learning based Parkinson's disease diagnostics. *Biomed Signal Process* 2022; 75: 103551.

182. Li H, Pun C, Xu F, et al. A hybrid feature selection algorithm based on a discrete artificial bee colony for Parkinson's diagnosis. *ACM Trans Internet Technol* 2021; 21: 1–22.

183. Athilakshmi R, Rajavel R and Jacob SG. Fusion feature selection: new insights into feature subset detection in biological data mining. *Stud Inform Control* 2019; 28: 327–336.

184. Lamba R, Gulati T and Jain A. A hybrid feature selection approach for Parkinson's detection based on mutual information gain and recursive feature elimination. *Arab J Sci Eng* 2022; 47: 10263–10276.

185. Pereira T, Ferreira FL, Cardoso S, et al. Neuropsychological predictors of conversion from mild cognitive impairment to Alzheimer's disease: a feature selection ensemble combining stability and predictability. *BMC Med Inform Decis* 2018; 18: Article number 137.

186. Zhao H, Xie J and Cao J. Early detection of Parkinson's disease by unsupervised learning from plantar bend data. In: *2022 IEEE 9th international conference on computational intelligence and virtual environments for measurement systems and applications (CIVEMSA)*, Chemnitz, Germany, 15–17 June 2022, pp.1–5. New York: IEEE. https://doi.org/10.1109/CIVEMSA53371.2022.9853703.

187. Rana A, Dumka A, Singh R, et al. Imperative role of machine learning algorithm for detection of Parkinson's disease: review, challenges and recommendations. *Diagnostics* 2022; 12: 2003.

188. Tan D, Pua Y, Balakrishnan S, et al. Automated analysis of gait and modified timed up and go using the Microsoft Kinect in people with Parkinson's disease: Associations with physical outcome measures. *Med Biol Eng Comput* 2019; 57: 369–377.

189. Samà A, Pérez-López C, Rodríguez-Martín D, et al. Estimating bradykinesia severity in Parkinson's disease by analysing gait through a waist-worn sensor. *Comput Biol Med* 2017; 84: 114–123.

190. Joshi D, Khajuria A and Joshi P. An automatic non-invasive method for Parkinson's disease classification. *Comput Meth Prog Bio* 2017; 145: 135–145.

191. Talitckii A, Kovalenko E, Shcherbak A, et al. Comparative study of wearable sensors, video, and handwriting to detect Parkinson's disease. *IEEE Trans Instrum Meas* 2022; 71: 1–10.

192. Chandrabhatla AS, Pomeraniec IJ and Ksendzovsky A. Co-evolution of machine learning and digital technologies to improve monitoring of Parkinson's disease motor symptoms. *NPJ Digit Med* 2022; 5: 32.

193. Kondragunta J, Wiede C and Hirtz G. Gait analysis for early Parkinson's disease detection based on deep learning. *Curr Directions Biomed Eng* 2019; 5: 9–12.

194. Ramdhani RA, Khojandi A, Shylo O, et al. Optimizing clinical assessments in Parkinson's disease through the use of wearable sensors and data driven modeling. *Front Comput Neurosci* 2018: 12: 72.