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Gornale, Shivanand, Kumar, Sathish, Siddalingappa, Rashmi and Hiremath, Prakash S. (2022) Survey on Handwritten Signature Biometric Data Analysis for Assessment of Neurological Disorder using Machine Learning Techniques. Transactions on Machine Learning and Artificial Intelligence, 10 (2). pp. 27-60.

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Transactions on Machine Learning and Artificial Intelligence - Vol. 10, No. 2
Publication Date: April, 25, 2022
DOI:10.14738/tmlai.102.12210.
Gornale, S. S., Kumar, S., Siddalingappa, R., & Hiremath, P. S. (2022). Survey on Handwritten Signature Biometric Data Analysis for Assessment of Neurological Disorder using Machine Learning Techniques. Transactions on Machine Learning and Artificial Intelligence, 10(2). 27-60.

Survey on Handwritten Signature Biometric Data Analysis for Assessment of Neurological Disorder using Machine Learning Techniques

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ABSTRACT

The handwritten signature is considered one of the most widely accepted personal behavioral traits in Biometric system. Handwriting analysis has wide applications in multiple domains such as psychological disorders, medical diagnosis, and recruitment of staff, career counseling, writer credentials, forensic studies, matrimonial sites, e-security, e-health and many more. In this paper, we recapitulate the state-of-the-art techniques and applications based on the handwriting signature analysis for the Assessment of Neurological Disorder using Machine Learning Techniques, In addition to this, achievements and challenges the scientific community should address. Thus, an integrated discussion of various datasets used, feature extraction techniques and classification schemes regarding Parkinson's disease (PD) and Alzheimer's disease (AD) is done and surveyed scientifically. The present research paper aims to provide an extensive review of scientific literature, ascertain vulnerable challenges and offer new research directions in the field.

Keywords: Biometric Data Analysis, Machine Learning techniques, Neurological Disorder, Handwritten Signature, Parkinson's and Alzheimer's disease.

INTRODUCTION

Biometrics is the Science and Technology of verifying the identity of individuals based on permanent and distinctive physiological measurements or behavioural traits. The various

biometric modalities can be broadly categorized as Physiological or Physical biometrics: This involves measures based on physical characteristics of an individual and is considered as a physiological biometric system and which includes the modalities like fingerprints, palm prints, face, iris, retina etc. Behaviological or Behavioural biometrics: This involves measurement based on the way (or action) in which a specific task has been performed by a subject termed as a behavioural biometric system which includes Body dynamics, Gait analysis, Keystroke, Voice and signature analysis etc. Chemical biometrics: this is an emerging field and includes measuring chemical clues such as stench and the chemical conformation of human perceptions like DNA.

The handwritten signature is a distinct behavioural biometric trait that is used to authenticate the uniqueness of an individual [13]. It is viewed as a Psycho-mechanic process achieved by the writer hand according to his/her brain signals [1]. It is one of the concentrated research areas where an individual's personality and neurological disorders can be detected /predicted. Handwriting analysis has broad areas of applications in various fields such as psychological disorder, medical diagnosis, conscription-of-staff, career-counseling, author identification[27]-[35],forensic studies, demographic studies, matrimonial sites, e-security, e-health and many more [1][2][3][12][21][22][23].

Handwriting is unique to each individual called-brain writing [4][5]. The neurological brain arrangement design brings one kind of neuromuscular movement that is the same for each individual with that precise personality mannerism. The handwriting reveals numerous belongings of an individual such as psychological problems, decency, unseen talents, health allied issues, experience etc., [6][9]. It reveals the psychological and physiological conditions of the patient; hence it is used as an investigative tool [7][8][14]-[19]. The symptoms of neurodegenerative disease like the Cerebral cortex, basal ganglia, and cerebellum are involved in the learning and accomplishment of handwriting [14][62].

Several studies have been carried out using offline and online handwritten signature analysis and assessment of neurological disorder diseases. The objectives of this survey paper are: 1. to deliver the approaches used in technology used for handwriting investigation. 2. Review the assessment of Parkinson's disease and Alzheimer's disease using Handwriting analysis. 3. To provide the symptoms and stages of Parkinson's disease (PD) and Alzheimer's disease (AD) diseases. 4. To provide the Machine learning systems used to assess neurological disorders. 5. To provide the frame- work for automatic assessment of Parkinson's and Alzheimer's diseases. 6. To provide the significant research gap/challenges. 7. To provide future research directions.

MATERIALS AND METHODS

Handwriting/Signature Analysis for PD and AD Assessment

Neurological disorder using handwriting/Signature has arisen as an interdisciplinary research issue and has concerned significant awareness from psychologists to neuroscientists and from physicians to computer scientists [49]. Handwriting/Signature includes rational planning, coordination, and execution abilities. Handwriting is a multifaceted movement involving perceptual-motor and cognitive mechanisms, the changes of which can be a promising biomarker for disease assessment [118]-[122]. Substantial variations in handwriting performance are a prominent feature of AD and PD disease [14]-[19], [53], [58]. Several investigators have also shown kinematic studies on the effects of old age and Parkinsonism on

the handwriting of personalities [83]-[92], [107]-[109]. The computer-aided analysis of the handwriting allows for identifying encouraging patterns that might be useful in PD recognition and assessment [117],[118]. Two major complications in the handwriting process upsetting PD patients are: decreasing the size of the characters (micrographia) not regular and Brady kinetic movements that lead to an increased movement duration, decreased speed and accelerations, and unhinged velocity and acceleration[93]-[106].

Related Work

Handwritten signatures are biometric individualities at the heart of deliberation in the scientific community. Over the last Forty years, the attentiveness in signature studies has grown-up progressively, having as its original reference the application of automatic signature authentication, as previously published reviews in three decades. Over the last ten years, the application of handwritten signature expertise has powerfully progressed and considerable research has captivated the opportunity to apply systems based on handwritten signature examination [58]. Some of the latest and relevant preceding work has been carried out is discussed in this section.

Marcos Faundez-Zanuy et. al.[12] have discussed the "applications and Future Trends in e-Security and e-Health using handwriting analysis"; and focused on the foremost endeavors and challenges that the scientific community should be address. Their work is a guide for future research.

Donato lmpedovo, Giuseppe and Pirlo G [14] have studied the "Dynamic Handwriting Analysis for the Assessment of Neurodegenerative Diseases: A Pattern Recognition Perspective", and addresses the most relevant results gained in the field of online (dynamic) analysis of handwritten trials by AD and PD disease patients. And they have emphasized the most cost-effective research instructions for te young scientists and technocrats.

Komal Saini and Manpreet Kaur[15] have carried out a "qualitative and statistical study to analyse the changes in various handwriting features due to old age and Parkinsonism". Handwriting samples from 50 healthy and old age persons and 25 individuals suffering from Parkinsonism were composed with their covenant. Features such as line quality blemishes, letter creations, an abbreviation of letters or their parts, nature of initial and terminal strokes, nature of connecting strokes, writing speed, overall size, and alignment were examined qualitatively and statistically through paired t-test. And they have concluded two features, namely retouching's and alignment, were least affected in the handwritings of patients suffering from Parkinsonism.

Moises Diaza et. al. [16] have proposed a "novel classification model based on one-dimensional convolution and Bidirectional Gated Recurrent Units" to evaluate the potential of sequential information of handwriting in categorizing Parkinsonian symptoms. One-dimensional convolutions are applied to raw categorisations and powerful features; the resulting arrangements are then nourished to BiGRU layers to accomplish the final classification. The projected technique outpaced state-of-the-art methods on the PaHaW dataset and attained modest results on the NewHandPD dataset.

URL: http://dx.doi.org/10.14738/tmlai.102.12210

C. D. Rios-Urrego et. al.[17] have assessed the prominence of diverse collections of features to prototypical handwriting shortfalls that appear due to Parkinson's disease; and how those features can distinguish between Parkinson's disease and healthy patients. The features based on kinematic, geometrical and non-linear dynamics analysis were estimated to classify Parkinson's disease and healthy patients. Classifiers based on K-nearest neighbours, SVM, and random forest were considered for classification and achieved the accuracy of up to 93:1% were obtained in classifying healthy non-healthy patients.

Seema Kedar, D. S. Bormane and Sandeep Joshi[18] have studied the online Analysis of Handwriting for diagnosis diseases such as Alzheimer, Mild Cognitive Impairment, Dysgraphia, Schizophrenia, Autism, Parkinson's disease and Mental illness. The Patient's handwriting has been acquired using WACOM's INTUOS digitalizing tablet. It is concluded that features correlated to motion, time and pressure are beneficial for the analysis of health and mental diseases.

Cascarano et al.[19] have studied the "Biometric handwriting analysis to support Parkinson's Disease assessment and grading system" in which 11 healthy subjects and 21 PD patients were registered in this study. Each subject was asked to write three different patterns on a graphic tablet while tiring the Myo Armband used to collect the muscle activation signals of the main forearm muscles; and then extracted some features related to the written pattern, the movement of the pen and the pressure exerted with the pen and the muscle beginnings. The computed features have been used to classify healthy subjects versus Parkinson's disease patients and to discriminate mild Parkinson's disease patients from moderate Parkinson's disease patients by using an artificial neural network and achieved remarkable rate-with classification accuracy higher than 90%.

Koteluk-O et al. [36] have discussed diverse models and the general development of ML and training algorithms. It summarizes the most helpful ML applications and tools in various medicine and health care branches. Authors have also addressed the innovative forecasts and intimidations of applying AI techniques as a progressive and computerized prescription tool.
U. Raghavendra et al [39] have deliberated the "state-of-the-art assessment of research on the automated diagnosis of five neurological disorders in the past two decades using AI techniques": epilepsy, Parkinson's disease, Alzheimer's disease, multiple sclerosis, and ischemic brain stroke using physiological signals and images. They have concentrated on up-to-date research articles on diverse feature extraction methods, dimensionality reduction techniques, feature selection, and classification techniques are studied.

Gennaro Vessioel[49] has studied the literature studying the application of "dynamic handwriting analysis in neurodegenerative disease assessment", in particular diseases like PD and AD diseases were studied. As the conclusion exposed issues for auxiliary exploration are emphasized.

Atilla Ünlü, et al. [53] have studied "Prognosis of Parkinson's Disease using handwriting analysis" through a new electronic pen and new features like inclination sensors, sensor electronics, pressure and vibration sensor (z-axis), pressure sensors in x and y-axis directions, ball pen for visual trace, trace on papere, etc., have recorded and gained the virtuous outcomes for diagnostics.

Mathew Thomas, et al. [232] have studied the evolution of the kinematic analysis of handwriting in PD and provided a summary of handwriting irregularities pragmatic in PD and future research directions. The analysis of numerous kinematic features of handwriting based on handwriting have exposed that patients with PD may have abnormalities in velocity, fluency, and acceleration in addition to micrographia. The recognition of irregularities in several kinematic constraints of handwriting has given rise to the term PD dysgraphia. Authors have concluded that micrographia to PD dysgraphia is indeed a paradigm shift and described added research directions for the young minds.

M. Tanveer et al. [221] have reviewed the 165 articles from 2005-2019 using several feature extraction and ML techniques. The ML methods are graphed under three core categories: support vector machine, artificial neural network, deep learning and collective approaches. Further, the authors have offered a detailed assessment of these three methods for Alzheimers with possible forthcoming directions.

Impedovo, D et. al.[227] have projected the handwriting-based procedure that assimilates handwriting tasks and a digitized version of typical perceptive and well-designed tests already accepted, tested, and used by the neurological community. An initial assessment of the protocol has been carried out to evaluate its usability. Successively, the protocol has been managed to more than 100 elderly MCI and match controlled subjects. The proposed model has provided a "cognitive model" for assessing the association between cognitive functions and handwriting processes in healthy and cognitively impaired patients.

De Gregorio G et. al.[228] have projected a multi-classifier approach predicting as many classifiers as the number of tasks, each producing a twofold output. The classifiers' outputs are finally shared by a majority vote to attain the ultimate decision. Experiments on a dataset involving 175 subjects used that 25 unlike handwriting and drawing tasks and 6 different ML techniques were selected among the most used ones. The literature shows that the best results are realized by choosing the subset of studies on which each classifier performs best and then joining the classifier's outputs on each task an accuracy of 91% with sensitivity and 83% with a specificity of 100%.

Rajib Saha et. al.[229] have studied the "Handwriting Analysis for Early Detection of Alzheimer's Disease and using the Deep learning technology" as the technical tool to recognize and categorize standard handwriting features of patients with AD. Variation auto encoder, a deep unsupervised learning technique has been applied. It is used to compress the input data and then to reconstruct it, keeping the targeted output the same as the input. This study is designed to successfully mining different features in the handwritten samples with the help of image segmentation and VAE reconstruction. And which can be used as a diagnostic tool for early detection of AD.

Wang, Z.; Abazid et. al.[230] , have "explored the online signature modality for characterizing early-stage Alzheimer's disease (AD)" and have focused on the analysis of raw progressive meanings learnt by the digitizer on signatures shaped during a replicated check-filling task. Sample entropy was exploited to measure the information content in natural time orders. The grouping of entropy values on two signatures for each person was classified with two linear classifiers SVM and LDA. They have concluded that, when integrated with pen pressure, the

URL: http://dx.doi.org/10.14738/tmlai.102.12210

altitude angle conveys decisive information on the wrist-hand-finger system during signature production for pathology recognition.

Li, X., Wang et. al.[231] have conducted the systematic study to classify differentially uttered genetic factor in blood samples from 245 AD cases, 143 mild cognitive impairment cases, and 182 healthy control subjects, and then compare these with DEGs in brain samples. Experiments have been carried with two discoveries autonomous AD blood datasets and performed a gene-based genome-wide association study to identify possible novel risk genes. Identified 789 and 998 DEGs common to both blood and brain of AD and MCI subjects respectively, over 77% of which had the same regulation directions across tissues and disease status, including the known ABCA7, novel TYK2 a TCIRG1. An ML classification perfect covering NDUFA1, MRPL51, and RPL36AL, associating mitochondrial and ribosomal function, was exposed distinguished among AD patients and controls with 85.9% of area underneath the curve 78.1% accuracy (sensitivity=77.6%, specificity=78.9%).

From the prose assessment, it is pragmatic that, the following are the research gap/challenges due to the Handwritings/ Signature pattern complexities and the variations of writing styles:

- The writing style changes according to the mood of a person and it depends on the language, because the personality traits may vary for different languages
- It is very usual that our signature is modified throughout the time and doesn't accompany us for our entire life, due to evolution, maturity and age of personality.
- It's still an open challenge to classify someone as a person who is meticulous and inattentive, immediate or sluggish to carry out the activities both specialized and day-to-day activities
- An increase in sugar cravings may be a side effect of the types of microorganisms (like bacteria) that live in our gut that can change in people with Parkinson's.
- Eating sugary foods makes their Parkinson's symptoms worse — but this has yet to be proven through scientific research.
- Diabetes has been revealed to intensify the risk of neurodegenerative conditions including Parkinson's.
- There are no measurable, impartial approaches for identifying Parkinson disease. Current methods of quantifiable examination by myograms grieve by imprecision and patient strain [51][53].
- Kinetic movement reflects in the subject's handwriting and to understand health and mental problems, it is essential to focus on how the subject writes instead of what subject writes. This also makes the process of handwriting analysis independent of any language.
- For Analysis of Parkinson's Disease, Alzheimer disease needs to develop multimodal traits using diverse modalities such as EEG, speech, handwriting, and brain images.
- A handwriting-based decision support system (DSS) is likely to assist clinicians at the point of care, providing a unique indicative tool while reducing the outlay of public health care.
- The performance of DSS with a larger cohort of subjects that includes severe Parkinson's disease patients with more grading systems like usual, Doubtful, Mild, Moderate and Severe.

- The pre-eminent perception of this line of research is the addition of new medical tools that can intensify the level of investigative precision.
- Interoperability is a silent difficult, data since data are typically obtained from different devices and different handwriting tasks.
- A longitudinal study should be achieved to comprehend the development of the disease in Parkinson's disease patients over time.
- The current research/algorithm still non-existence of features such as the stage of disease, the medical treatment, sternness of disease and so on.
- There should be automated system based handwriting to support the forensic document specialists for substantiating the documents like a will, property document, bonds etc.
- Innovative health-based claims using text, drawings, and touch screen collaboration with Signatures for analysis of diseases and even for revealing of stress and exposure of drug substance openings.
- An expert system based on deep learning strategies needs of accurate to model the handwriting deficits of PD and AD diseased patients.
- Development of an effective and efficient handwriting based decision support tool is desirable. It can provide a non-invasive, real-time, and low-cost solution to support the standard clinical evaluations carried out by human experts.
- Machine Learning-Based Computer-Aided Diagnosis for Impulsive revealing of Neurological Disorders and Remotely admittance by Non-expert Clinicians
- Non-representative, poor-quality, immaterial features, or inadequate amount for exercise reduces the process's competence, which yields the then lower accuracy.
- Robust & coherent algorithms need to be developed for the accuracy improvement in the impost of PD and AD disease using handwritten signature.

Search Strategy

The assessment involved a systematic search, which was navigated in April/May-2021. To bargain the most suitable studies, we searched the published work in the literature using search engines published in the Web of Science, PubMed, Scopus databases, IEEE Transactions, ACM, Elsevier and other digital libraries which are publically published available along with the medical reports and studies. These published work/reports focus on Handwritten Signature Biometric Data Analysis for Assessment of Neurological Disorder using Machine Learning Technique.

A comprehensive search approach was applied by using frequent key words and mixtures. Some of the possible combinations of keywords used for searching are:

- Handwritten Signature Biometric Data Exploration for Assessment of Neurological Disorder
- Assessment of PD and AD disease using handwritten signature
- Offline and online handwritten signature of the evaluation of PD and AD diseases
- Handwritten Signature Biometric Data Analysis for the assessment of Parkinson's and Alzheimer's diseases using machine learning techniques
- Symptoms of PD and AD diseases based on handwritten signatures

URL: http://dx.doi.org/10.14738/tmlai.102.12210

Selection Criteria

The article congregation process was based on the PRISMA statement [235]. The formative factor in the inclusion criteria includes any published full-text journal article on the usage of machine learning for airing or analysis of neurological disorders. At the initial screening stage, many studies are found during broad search strategy, but they are beyond our scope of the reviews and were excluded after airing the titles, abstracts, or full texts of articles obtained from the search. These Studies were considered for review if: (1) they are original or review articles, (2) the text available in English, and (3) Machine learning techniques were used to study handwriting for the assessment of Parkinson's and Alzheimer's diseases. In this study, nearly 278 research studies have been carefully assessed for eligibility. Eighty-five (85) reviews out of the 278 records were excluded, due to the following reasons: 1-The objective and study of the work not adequately defined, 2-Studies those are not relevant to the specific research question/problem domain, 3-articles that have not used machine learning as the leading techniques and 4-relevant studies, but PD and AD diseases using handwritten/handwritten signature is not the primary disorder assessed. The PRISMA flow diagram as shown in Fig.1 summarizes the above-mentioned methodical literature review process. Table 1 provides the key objects of the inclusion and elimination measures of the study.

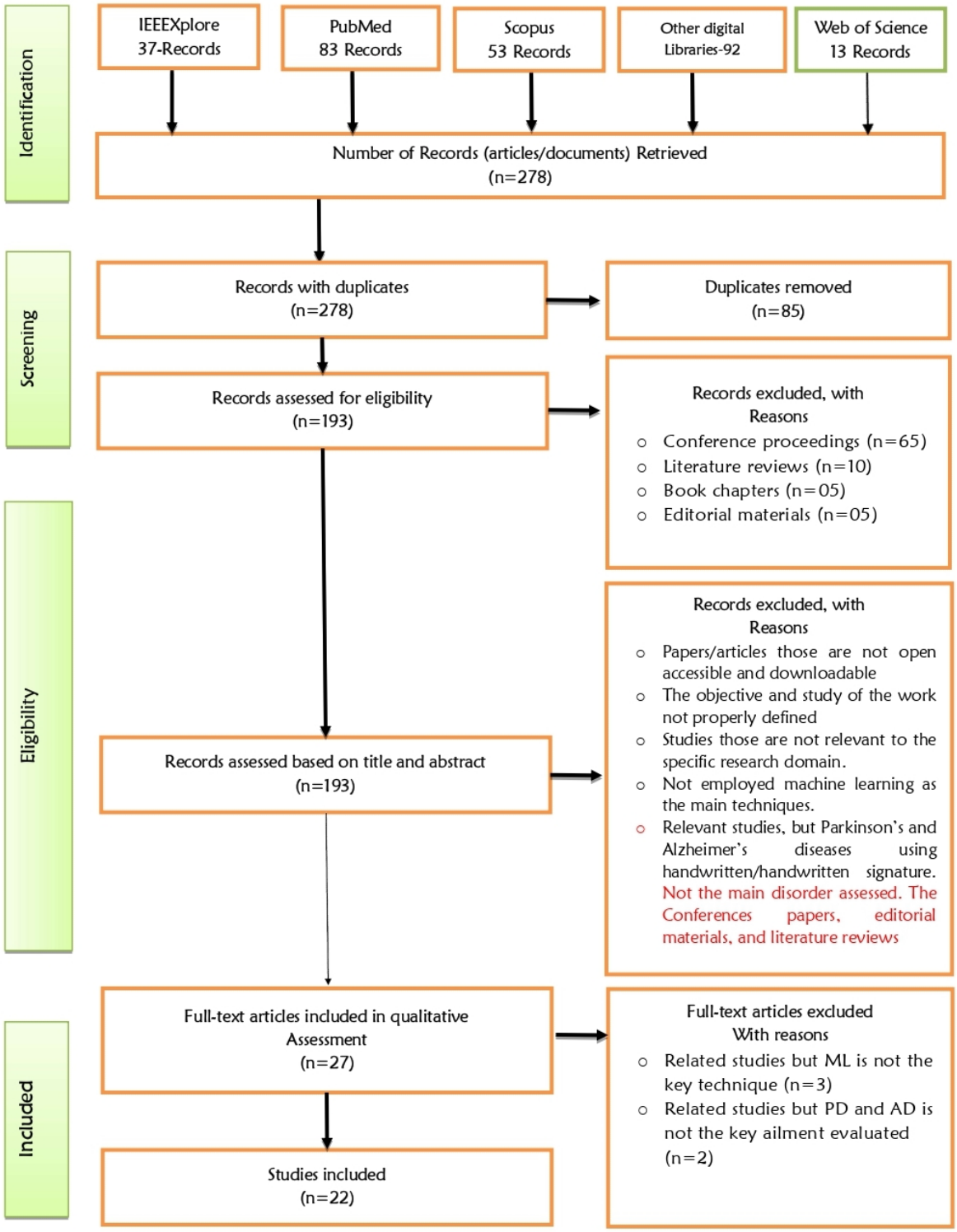

Fig 1: PRISMA flow diagram showing the summarized above-mentioned systematic literature review process

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Table 1. Inclusion and exclusion measures of the study

Inclusion Measures for the study	Exclusion Measures for the study
1. Articles which are available in the English linguistic. 2. Articles available inside the last two more decades. 3. Papers/articles those are open accessible and downloadable. 4. Studies that utilized behavioural Biometric data i.e. Offline and online signature. 5. Research work related to machine learning as the main techniques. 6. Research work related to Neurological disorder in particular Parkinson's and Alzheimer's diseases.	1. Articles which are written/published in Non-English languages 2. Papers/articles those are not open accessible and downloadable 3. The objective and study of the work not properly defined 4. Studies those are not pertinent to the specific research domain. 5. Studies those are not employed machine learning as the main techniques. 6. Relevant studies, but PD and AD diseases using handwritten/handwritten signature not the basic disorder judged.

Quality Assessment:

The survey aims to incorporate a wide variety of studies associated to handwriting analysis in patients with PD and AD diseases, indecisive from reviews on micrographic to kinematic handwriting studies for diagnostic and therapeutic purposes, and re-learning of handwriting using machine learning techniques, because of the heterogeneity of the articles considered for offline and online signature analysis for PD and AD diseases.

Data Extraction

The Data extraction and collection is one of the phase PRISMA study, the data abstraction stage, 18 articles were assessed critically for the assessment of PD and AD diseases using handwritten signature, and the following actualities were mined from the studies:

- Author(s)
- Source(s) of the research data,
- Data collection/ assessment instrument/device
- Computer-Aided Analysis(CAD) using Machine learning models
- Best accomplishment model(s) and the significant finding(s)
- Future research directions for the young minds

i. Results and Discussion

Based on the primary research on machine learning techniques in the behavioural assessment of PD and AD diseases exhibited in the most cited publication occurrences across the years. With the increasing application of AI and ML in healthcare studies; the studies, include the research publications/studies for more than two decades. Nevertheless, with the newly augmented venture of Machine learning techniques across various fields there is increasing tutoring for intelligent tools for accurate assessment of Neurological disorders. The articles contributing to machine learning-based assessment of the diseases for the last decade (2010 to 2021) are as shown in Fig 2.

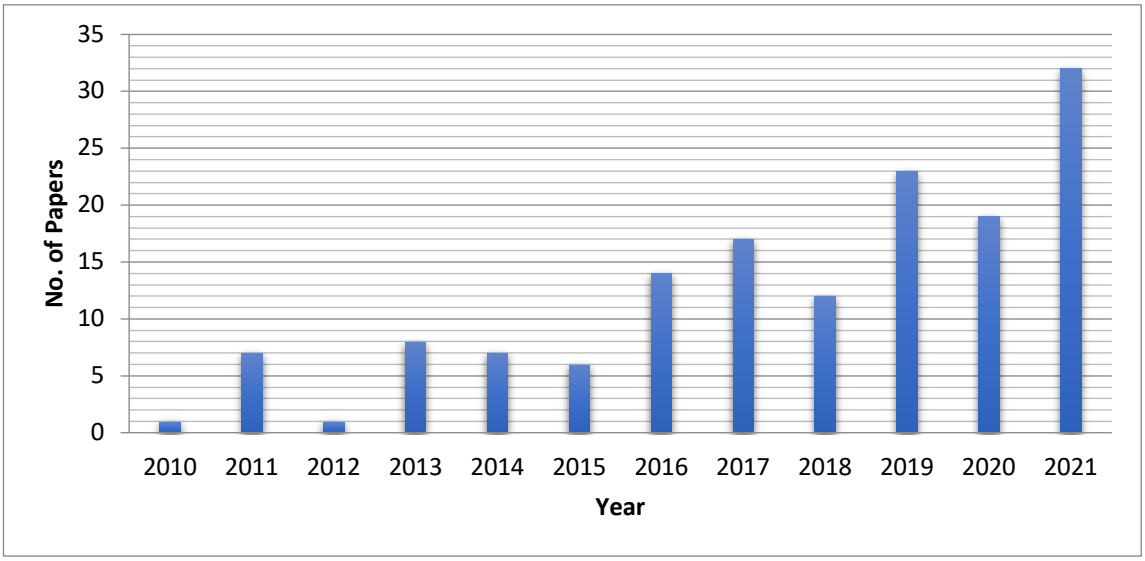

Fig 2. Publications distribution over the last one decade (2010-2021)

Machine Learning Techniques for Assessment of Neurological Disorders

Artificial Intelligence (Al) focuses on manipulating calculation techniques with advanced investigative and extrapolative facilities to process all data types [36]. The comprehensive review of publications related to artificial intelligence (AI) applications in healthcare for the year 2020 has been predicted in [38], and made PubMed search using the terms, "machine learning" or "artificial intelligence" and "2020", restricted to English language and human subject research as of December 31, 2020. This search resulted in an initial pool of 5885 articles [38] related to AI and ML are predicted.

Machine Learning procedures are recycled to perform calculations and predictions [37]. Machine learning is a subfield of artificial intelligence science that enables the machine to become more operative with training knowledge. Three primary learning models are supervised, unsupervised, and reinforcement learning. Learning models are differ depending on the input data type and need have numerous systems [36]-showed in Fig 3.

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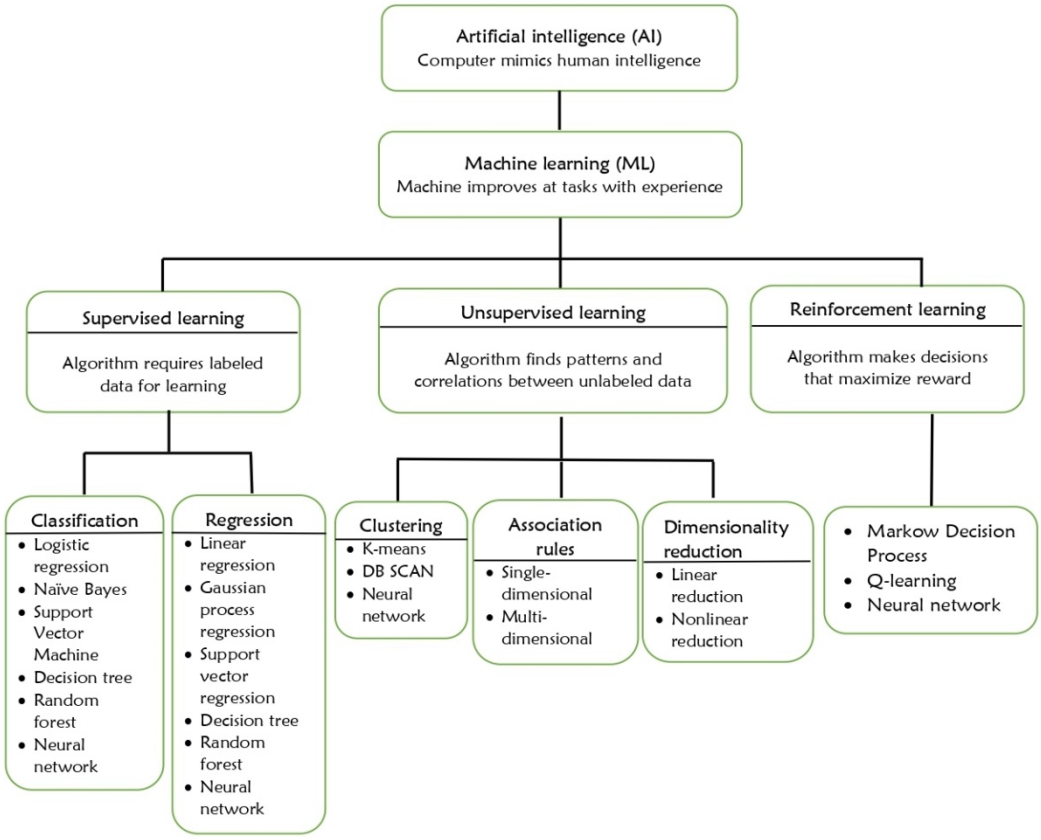

Fig 3. Supervised learning, unsupervised learning, and reinforcement learning

Supervised learning: Supervised learning is a type of machine learning in which machines are proficient using well "labeled" training data, Based on that data, machines predict the output. [158],[159].

Unsupervised Learning: Unsupervised learning is a machine learning technique in which the users do not need to supervise the model. Instead, it allows the model to work on its own to discover patterns and information that was previously undetected [158]

Reinforcement learning (RL) is an area of machine learning concerned with how intelligent agents ought to take actions in an environment to maximize the notion of cumulative reward. Reinforcement learning is one of three basic machine learning paradigms, alongside supervised learning and unsupervised learning [160][161]. Different types of machine learning techniques can play an essential role in building operative models in various application areas according to their learning capabilities, depending on the nature of the data and the target outcome. The comprehensive ML technique that can be applied to improve the intelligence and abilities of a data-driven application and specific algorithms suited different supervised, unsupervised, and Reinforcement learning models with their prediction are elaborated in [148]-[155] and the real-world applications and research guidelines in machine learning are forecasted in [141]-[146],[156],[157],[162],[233][234] for young technocrats.

AI and ML techniques in a automated fashion can support neurologists, neurosurgeons, radiologists, and other medical providers to make better clinical conclusions. Neurological

disorders are diseases connected with bordering and central nervous organisms. The common indications include muscle weakness, paralysis, seizures, pain, poor coordination, and loss of perception [40]. There are > 600 diseases related to the nervous system such as brain tumour, PD, AD, multiple sclerosis (MS), epilepsy, dementia, headache disorders, neuro infections, stroke, and traumatic brain injuries and many others. [39].

Dementia is typically progressive in the environment. It disturbs the various cortical functions: memory, location, rational, calculation, language, understanding, judgment, and learning ability. Alzheimer's disease is the leading communal cause of dementia [126]-[128].

Epilepsy is a lingering neurological sickness. The epilepsy definition requires at least one epileptic seizure [129]-[133]. The summaries of Computer-Aided Diagnosis for detecting Epilepsy with additional features, classifiers along with detecting Epilepsy with extra features, classifiers and accuracy are predicted in [39].

Multiple Sclerosis (MS) a disorder began by a condition called provocative demyelinating of the nervous system is the most common among all neurological disorders. MS origins infirmities in young grown-ups. The analysis of MS is typically done by magnetic resonance imaging. No treatments are available for this disease [134]-[135]. The summary of Computer-Aided Diagnosis (CAD) systems for the detection of MS (modality: MRI) with different methodology, classifiers along the accuracy are predicted in [39].

Parkinson's disease is an enduring neurodegenerative disorder frequently categorized by the presence of mainly motor symptomatology, but it can have non-motor *hyposmia, paraesthesia, depression, and pain*. Parkinson's disease is a world-wide sickness with the rate of 4.5–19 per 100,000 of populace per year for both women and men of all ages [41-46]. PD and AD diseases, affect brain areas structure and utilities, resulting in liberal reasoning, functional, and Behavioural deterioration. Parkinson's disease is caused by the erosion of the dopaminergic nigrostriatal neurons of the basal ganglia, mainly resulting in motor deficits: akinesia, bradykinesia, rigidity, and tremor are naturally perceived. The summary of Computer-Aided Diagnosis (CAD) systems for the detection of PD (modality: MRI, EEG) with different features, classifiers along the accuracy are predicted in [39].

Alzheimer's disease is considered by short-range memory loss in its initial stages, followed by a enlightened failure in other cognitive and behavioural functions as the disease advances: therefore, the main feature of AD is mostly of cognitive nature [47]-[49]. In general, AD patients produce leisurelier, less smooth, less synchronized and less regular handwriting activities than their healthy counterparts [79]-[82], [113]. The summary of CAD systems for the detection of AD (modality: MRI) with other techniques, classifiers and accuracy are predicted in [39].

Symptom of Parkinson's disease (PD)

PD is a brain illness that leads to trembling, toughness, and difficulty with walking, balance, and coordination. As the disease evolves, people may have trouble rambling and speaking. They may also have psychological and behavioural changes, sleep difficulties, sadness, reminiscence problems, and fatigue [54]. Parkinson's Disease is usually identified by the first motor indications [114],[115]. In particular, leisureliness, lessening in the amplitude of repeated actions and micrographia tremor, and inflexibility are observed, Parkinson's Disease patients,

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if compared to controls, write smaller letters, and apply less pressure, and need extra performance time[62]-[78].

Parkinson's disease occurs when nerve cells, or neurons, in an area of the brain that control movement become impaired and/or die. Usually, these neurons produce an essential brain chemical known as dopamine. When the neurons die or become damaged, they produce less dopamine, which causes the movement problems of Parkinson's. It has four main indications:

- Tremor (vibrating) in hands, arms, legs, jaw, or head
- The arduousness of the limbs and trunk
- Leisureliness of accountability
- Impaired steadiness and synchronization, sometimes leading to falls

Other signs may include depression and other dynamic changes; difficulty in believing, mastication, and speaking; urinary problems or constipation; skin problems; and sleep disruptions. Another symptom is variation in sugar level in the body. The brain is dependent on a type of sugar, known as glucose, as its primary fuel. It is also the utmost energy-demanding tissue, using one-half of all the sugar energy in the body. When there isn't enough sugar around there are some very severe complications [50][55]-[57]. There are currently no blood or laboratory tests to diagnose non-genetic cases of Parkinson's disease. It is based on a person's medicinal antiquity and a neurological examination. Development after initiating medication is another important symbol of Parkinson's disease.

The diagnosis process of PD is expensive and time-consuming for patients, caregivers, and the health system [110]-[112]. Automatic handwriting analysis could help support the process to diagnose and monitor the patient's neurological state.

Symptom of Alzheimer's disease (AD)

Alzheimer's disease is a progressive condition, memory loss is a crucial feature, and this tends to be one of the first signs to grow. The indications seem progressively over months or years. If they progress over time, a person may involve medicinal consideration, as this could indicate a stroke [219], [220]:

- Memory loss: A person may have trouble captivating new information and memorizing information. This can lead to repeating conversations, trailing substances, forgetting about events and missing peripatetic or attainment.
- Cognitive deficits: A person may experience struggle with perceptive, multifaceted tasks, and decisions.
- Problems with recognition: A person may convert to less intelligent to distinguish faces or substances or less able to use basic tools.
- Problems with spatial awareness: A person may have trouble with their stability, trip over, or spill things more often, or they may have difficulty in orientating clothing to their body when getting dressed.
- Problems with speaking, reading, or writing: A person may develop difficulties with discerning common words, or they may make more speech, spelling, or writing errors.
- Personality or behavior changes: A person may experience changes in behavior i.e. flattering distressed, annoyed, or nervous more often than before, a loss of interest in or motivation for activities.

In [219], authors have recommended that a transformation in the person's sense of humour might also be an early symptom of Alzheimer's. Alzheimer's disease can range from mild to severe. Mild Alzheimer's disease -develop memory and cognitive difficulties that may include the following: taking longer than usual to perform daily tasks, difficulty handling money or paying the bills, nomadic and getting lost, experiencing character and performance changes, such as getting upset or angry more easily, hiding things, or pacing. Moderate Alzheimer's disease- the parts of the brain accountable for verbal, senses, reasoning, and realization are damaged. Severe Alzheimer's disease signs and masses are present throughout the brain, triggering the brain tissue to psychiatrist substantially. This can lead to the inability to communicate, dependency on others for care, being incapable of leaving bed at all or most of the time.

There is no recognized treatment for Alzheimer's disease. It is not possible to reverse the death of brain cells. Treatments can, however, relieve its indications and progress quality of life for the person and their family and caregivers. The following are important elements of dementia care: effective management of any conditions occurring alongside Alzheimer's activities and day-care programs, involvement of support groups and services. There is currently no treatment, but drugs and other therapies can help deliberate or ease the cognitive, emotional, and behavioural symptoms and improve the person's quality of life.

The analysis process of AD is again affluent and time-consuming for patients, caregivers, and the health system. Automatic handwriting analysis could help to support the process of diagnosing and monitoring the patient's neurological state [221]-[226].

Biometric Data behind Handwriting

a. Features of Handwriting/Signature

Off-line (static) features: The common offline structures commonly used for script analysis for the assessment of Behaviour and illnesses are. Line Quality, Word and Letter Spacing, Size Steadiness, Pen Highs, Initial and fatal strokes, Correcting, Tremor, Linking Strokes, Letters Complete, Cursive and Printed Letters, Pen Pressure, Slant, Baseline Habits, Embellishments and Accompaniments, Accent Location, Position Signature, Legibility and many more. Some of the traditional methods are used to analyze for the detection of neurological disorders. The Six-item Clock-Drawing Scoring System (CDSS): a rapid transmission for intellectual impairment in Parkinson's disease [166]-[171], [177]. Mini-Mental State Examination delivers numerical assessment of cognitive changes over time a time; and it is mainly used to assess brain injury, cardiac Dysfunction, Parkinson's disease, Neurologic Reintegration and hit recovery [172]-[175], [177]-[180]. Montreal Cognitive Assessment test in patients with fibromyalgia scrutinizes the association of that performance with physical and cognitive performance [176]. The synthetic house-tree-person drawing test is a projective quantity that is mainly intended to measure precise, multifaceted behavior characters. It is extensively used in mental difficulties and psychological sicknesses such as mental crisis involvement [181]-[182].

Online (Dynamic) features: Operational handwriting permits apprehending several possessions of the moving pen in a real time system like time stamp, pressure, Speed, Velocity, Acceleration, Width, height, position, Button status, altitude, displacement etc.; which are not possible to capture in offline handwritten signature [14]15][17][18],[183]. The acquisition strategies scrupulous in online handwriting allow capturing various properties of the moving pen [136].

URL: http://dx.doi.org/10.14738/tmlai.102.12210

b. Datasets

Various databases used in proceeding work based on off-line (static) features of handwriting, which can be analyzed after the writing process has already happened, Dynamic handwriting (on-line-Dynamic) analysis deals with those features that can be acquired during the writing process. This section discusses the various databases were used in the proceeding research work.

1. PaHaW-Database [16], [123]

The "Parkinson's disease Handwriting Database (PaHaW)" consists of manifold handwriting trials from 37 parkinsonian patients (19-Male/18-Female) and 38 sex and age harmonized controls (20 Male/18 Female). The database was developed in support of the Movement Disorders Center at the First Department of Neurology, Masaryk University and St. Anne's University Hospital in Brno, Czech Republic. University and St. Anne's University Hospital in Brno, Czech Republic. Each person was requested to complete a handwriting task according to the prepared filled pattern at a hassle-free speed. The completed task sheet is shown on the right. The completed template was shown to the persons; no limitations about the number of recurrences of words in tasks or their height were given. A tablet was overlaid with an empty paper template and a conventional ink pen was held in a typical style, allowing for instant full graphic feedback. The signals were chronicled using the Intuos 4M (Wacom technology) digitizing tablet with a 150H sampling frequency [16],[123].

2. NewHandPD [16][124][125]

The NewHandPD database is an extension of the previous HandPD corpus. The first database consisted of images from two drawing tasks, i.e. the typical spiral cognitive test and a modified spiral (\meander") test performed by healthy individuals and people with Parkinson's disease. However, the new corpus, NewHandPD, contains offline images and online signals (time-based sequences). The handwriting signals were acquired through a technology other than a tablet, i.e. an electronic smart pen (BiSP). NewHandPD contains images and dynamic data from 31 patients and 35 healthy people. The gender of the participants was reasonably balanced (39 males and 29 female), while most of them were right-handed writers (59 of 66 participants)[16][124][125].

3. Created Own Database (Available freely for non-Commercial research Purpose)[54]

A new online handwriting database which includes 20 subjects and the selected participants were 20 healthy young men, with the following details: Age: 21.3 ± 3.5 years, Weight: 71.9 ± 7.5 kg, Height: 175.6 ± 7.2 cm, Body mass index: 23.2 ± 3.4. They were Sport Sciences and Physiotherapy students who performed physical activity a minimum of 3-4 times per week. Participants were familiar with all testing procedures. The study protocol received approval from the Ethics Committee of the Tecno Campus-Universitat Pompeu Fabra (Matar6, Spain) and adhered to the tenets of the Declaration of Helsinki.

4. Created Own Database [17]

The data were collected with aWacom Cintiq 13 HD tablet, with visual feedback to the patients and a sampling frequency of 180 Hz. The tablet captures six di_erent signals: horizontal position (x(t)), vertical position (y(t)), azimuth angle, altitude angle, distance to the tablet surface (z(t)), and pressure of the pen. For this study, the participants drew an Archimedean spiral following a predefined template (Figure 1), which was displayed on the tablet. Participants were

requested to draw the spiral between template lines and avoid crossing them. Three different participants: 23 years old subject (left), 65 years old subject (middle), and 73 years old Parkinson's Disease patient with an MDS-UPPD-III score of 64 (right).

5. Created Own Database[19]

32 participants (21 males, 11 females, 71.4 ±8.3 years old) were enrolled for the experiment. In detail, the participants were composed of 21 PARKINSON'S DISEASE subjects (17 males and 4 females, age: 72.1 ±8.3) and 11 healthy ones (4 males and 7 females, age: 70.2±10.2 years old); the healthy group was selected to match the age of the Parkinson's disease one. The Parkinson's disease group was subsequently divided into mild and moderate subgroups according to the degree of the disease. The subgroups were composed of 12 mild patients (9 males and 3 females, age: 70.5±10.0) and 9 moderate ones (8 males and 1 female, age:73.8±6.0).

6. Created Own Database[15]

Handwriting samples from 50 vigorous old age persons and 25 individuals suffering from Parkinsonism were collected with their accord. Information such as age, sex, educational qualification, and occupation was acquired from each subject. Handwriting topographies such as line quality defects, letter formations, an abbreviation of letters or their parts, nature of initial and terminal strokes, nature of connecting strokes, writing speed, overall size, and arrangement were examined qualitatively and statistically done through paired t test.

7. ParkinsonHW (Publically available for Research Community)[137]

This database is created by gathering 62 Parkinson's disease patients and 15healthy individuals. From all subjects, three types of handwriting recordings, namely Static Spiral Test, Dynamic Spiral Test, and Stability Test on Certain Point were measured. The images of the spirals drawn by patients are also provided. Three Archimedes spirals appeared on the graphic tablet in the SST test, and patients were asked to retrace them. Unlike SST, in the DST test, the Archimedes spiral appeared and disappeared at specific time stamps. This forced the patient to keep the pattern in mind and continue drawing. In the STCP test, there was a certain red point in the screen and the subjects were asked to hold the digital pen on that point without touching the surface. The purpose of this test was to determine the patient's hand stability or hand tremor level.

8. ISUNIBA[138]

The ISUNIBA dataset contains handwritten trials self-possessed from 41 people: 12 HC and 29 AD patients. Each member was demanded to write the word "mamma" (i.e., Italian of "mom") over diverse recording sessions. The ideal of the word mom, indistinguishable to all the authors, is related to the reputation of this word, and the figure associated with it. And it is also repeated with high frequency by subjects in an advanced state of AD.

9. HandPD dataset[139]

The inventive HandPD dataset included handwritten/drawn tribunals from healthy and Parkinson's disease persons and was mainly intended for static analysis. The dataset was further prolonged for dynamic analysis and it contained data from 66 individuals (35 healthy controls and 31 Parkinson's disease patients). The new prolonged version is called "NewHandPD", captured by a biosensor smart pen (BiSP).

URL: http://dx.doi.org/10.14738/tmlai.102.12210

10. EMOTHAW [140]

It does not include Parkinson's disease and/or AD patients, but tasks assumed are characteristically used in studies dedicated to Parkinson's disease and AD. It could be helpful for assessment purposes only.

Challenges towards the Datasets

- A bench database/dataset comprising a statistically substantial number of patients and a set of momentous tasks significantly restraints research growth.
- There is the nonexistence of research on non-Western languages and local languages.

PROPOSED AUTOMATED FUNCTIONAL MODEL BASED ON MACHINE LEARNING

AI and ML techniques have grown-up speedily in current years in the context of data analysis and figuring that naturally allows the applications to function intelligently. These learning methods in an automatic stylishness can promote neurologists, neurosurgeons, radiologists, and other medical benefactors to make better clinical conclusions. These techniques help develop a fully automated method that may be efficient in time, has less computational complexities, reduced manual interactions, and better visualization & quantification [142]. The typical functional block diagram of Machine Learning is shown in figure-2, which is based automated system and consists of 5 stages: (1) Data acquisition (2) Pre-Processing (3) feature extraction (4) Feature dimensionality reduction/optimal feature selection/ranking and (5) classification. The Fig 4. Graphical representation of machine learning-based automated structure.

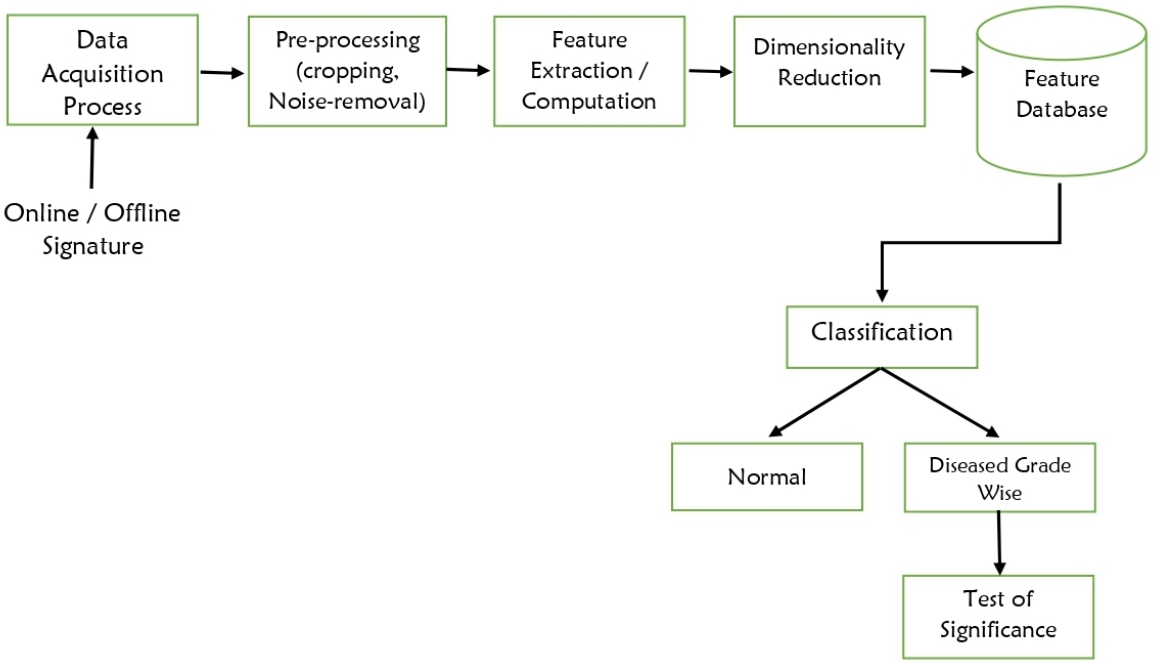

Fig 4: The distinctive figure of Machine Learning based automated structure

Data Acquisition

Data attainment can be chosen as the accomplishment of fetching an image/data from a particular source, which is further handled to get new and restored image/data [163][164].

Acquisition of Handwriting/Signature is based on off-line (static) features of handwriting, which can be analyzed after the writing process has already occurred: dynamic handwriting (on-line-Dynamic) analysis deals with those features that can be acquired during the execution of the writing process.

An offline (static) handwritten/signature is a straight forward process: Each signature is to be captured on a white A4 paper sheet using ball pen. Further, the papers with sample signatures have been skimmed using a high resolution scanner or camera and stored in a digital device [61]. Whereas in dynamic handwriting (on-line-Dynamic) analysis various digitized devices are used to capture the data and they are: Wacom Cintiq 13 HD tablet[17], Intuos WACOM Series 4-digitizing tablet[18], naturaSign Pad Comfort, Wacom STU-430, Wacom STU-530, NaturaSign Pad Colour SIGNificant ColorPad 6, Wacom DTU-1031x, Wacom DTU-1141, Wacom PL-1600, Wacom PL-2200, etc.,

Pre-processing

The improvised data assimilated by the device are generally improved employing standard signal/Image processing algorithms: filtering, noise reduction, and smoothing. The basic idea behind enhancement techniques is to bring out detail that is concealed, or to highlight certain features of interest in an image [14][165].

Feature Extraction

It is one of the significant components of the proposed work model for the analyzing handwritten signatures for the neurological disorder using machine learning techniques [184]. We compute features of captured offline/online signatures in this stage, which results in assessment accuracy with a very modest classification unit. Some of the generic features are: Zernike features: Zernike moment is one kind of special complex moment, based on orthogonal functions called Zernike polynomials. Zernike moments have the characteristics of rotation invariance and have been widely used in the field of target recognition. These geographies help represent possessions of an image/data with no overlay and to designate shape features, including determining the likenesses between shapes represented by their features area, eccentricity, perimeter etc. The Statistical features Includes accumulating, framing, determination & amplification of data. Mean-variance, Skewness, and median etc. Local texture descriptors that concentrate on isolated contributions of small regions. Haralick features help in gauging the texture of the image in terms of entropy, angular second moment, correlation, inverse difference moment etc. A Tamura texture feature includes contrast, directionality and coarseness of an image [185]-[195].

Dimension Reduction/Optimal feature Selection/Ranking

Feature assortment and dimensionality reduction are grouped. While both methods are used for reduce the number of features in a dataset; there is an important difference between them Feature selection is simply selecting and excluding given features without changing them Dimensionality reduction transforms features into a lower dimension. The Feature Selection often eliminates features with missing values, low variance, highly correlated features. The Univariate feature selection, Recursive feature exclusion and Feature selection using select from model [196]. The Dimensionality reduction method keeps the most applicable variables from the original dataset. By finding smaller sets of new variables, each grouping of the input variables, comprising basically the same information as the input variables. Some of the

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standard techniques are Missing Value Ratio, Low Variance Filter, High Correlation filter, Random Forest, Backward Feature Elimination, Forward Feature Selection, Factor Analysis, Principal Component Analysis, Independent Component Analysis, Methods Based on Projections, t- Distributed Stochastic Neighbor Embedding (t-SNE), Uniform Manifold Approximation and Projection, Linear Discriminant Analysis [197][198][199][200][201]etc.,

Classification

A classifier in ML is an algorithm that robotically orders or classifies data into one or more sets of "classes." ML techniques accommodate to systematizing tasks that had to be done manually beforehand. Many ML algorithms exits that range from simple to complex in their approach and together provide a robust library of tools for analyzing and forecasting patterns from data. Different classifiers like K-Nearest Neighbor, Decision Tree, Support Vector Machine, Multilevel Slice, Minimum Distance, Artificial Neural Networks, Convolution Neural Network, Deep Learning Maximum Likelihood etc., are used to categorize the input image/data based on features. From the preceding research work on various classifiers used for the classification of data, it is observed that the appropriate classifiers are dependent on the type of data and type of applications [142], [202]-[210].

VALIDATION AND TESTING THE RESULTS

After sample data has been collected through an observational study or experimentation, statistical implication consents analysts to measure indication in favour or some prerogative about the population from which the sample has been drawn. The extrapolation methods used to support or discard entitlements based on sample data are known as tests of significance:

- *Statistical Test of Significance:* The significance test is done to normalize whether the consequences of the experiments are statistically significant or not. The common tests like the Chi-square test, t-test and ANOVA, are executed to confirm the implications of the contemporary work [211]-[218].
- *The "Chi-square (χ2)"* test signifies a useful technique of equating experimentally gained results with those to be anticipated hypothetically on a particular hypothesis. Thus Chi-square is a degree of actual deviation of the experiential and expected frequencies. It is very perceptible that the position of such a measure would be very prodigious in sampling studies where we have perpetually to study the deviation among theory and fact.
- *t-test:* It is carried out when any experiment is trying to draw an assessment or find the difference between one another, and then you need to work on the two-sample T-test, to find the substantial difference between the two variables
- *ANOVA test:* This test is carried out when any experiment tries to draw an association or find the difference between one category and another continuous variable.

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Handwritten signatures are biometric qualities at the centre of deliberation in the scientific community. From the last 40 years, the awareness in signature studies has grown-up progressively, having it as original orientation the application of involuntary signature confirmation, as formerly published reviews in 1989, 2000, and 2008 bear witness. The handwritten signature is measured as one of the most extensively acknowledged personal behavioural traits in the Biometric system. Handwriting analysis has the wide applications in

various fields such as psychology, medical diagnosis, and enrolment of staff, career counselling, writer identification, forensic studies, matrimonial sites, e-security, e-health and many more. In this view , we summarized the state-of-the-art techniques and solicitations based on handwriting signature analysis for Assessment of Neurological Disorder using Machine Learning Techniques achievements and trials/problems that should be addressed to the scientific community.

In future there is still a scope to develop a fully automated method that may be efficient in time, has less computational complexities, reduced manual interactions, better visualization & quantification.

Future research directions are:

- A Proof-of-Concept (POC) solution that will leverage advanced Artificial Intelligence technology and deep machine learning to learn from an extensive database of Handwriting signatures of Parkinson's Disease and Alzheimer disease cases, thereby enabling doctors to make better assessments of disease and make appropriate recommendations.
- There should also be cloud-based system for automatic diagnostic tool for analyzing neurological sicknesses using the Internet of things (IOT).
- The solution should consist of both the AI component and an app platform that will allow patients and care-givers to access information on neurological disorders and treatment options.
- The predictive model should provide doctors with extra intelligence a dependable tool to make accurate predictions for future days.
- There is a demand in the technology where patients should be empowered to take ownership of their treatment options by educating patients on what they should note of before deciding on higher treatment.
- Developing a large benchmark dataset involving a statistically significant number of patients, and a set of substantial tasks, is still one of the major open issues in the pattern recognition community working in this field.
- There is an excessive need to first explore and progress tools for measureable annotation of datasets, followed by computerized systems for approximation in disease harshness.
- Improvement of feature and modality level synthesis outline for the effortlessness analysis for diseases.
- Hence an attempt has been made to put just another tiny brick into the wall of research on Handwritten Signature Biometric data analysis to finding and order of neurological diseases, particularly PD and AD diseases. So it is a crucial footstep in computer-aided analysis to identify the extremity of the conditions.

URL: http://dx.doi.org/10.14738/tmlai.102.12210

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