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Advancements in Machine Learning and Deep Learning for the Detection of Neurological Disease: Parkinson's Disease Case Study

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Abstract
Parkinson disease (PD) is a neurological disease that worsens with time and is distinguished by the degeneration of dopamine-producing neurons in the brain, especially in the Substantia Nigra. This neuronal loss lead to the spectrum of motor and non-motor symptom's, like postural instability, muscle rigidity, bradykinesia, tremors, autonomic dysfunction, sleep disturbances, mood disorders, cognitive changes, sensory symptoms, and others. The disease progression through stages from mild to severe significantly impacts patients' quality of life, affecting daily activities and functional independence. For immediate treatment and management of PD, early and precise detection is essential. Traditional detection methods have limitations, prompting the exploration of ML and DL to increase detection accuracy. ML methods like Neural network, Random Forest, Support Vector Machines (SVM), are employed to analyze diverse datasets including clinical assessments, genetic profiles, imaging results (MRI, PET), and voice recordings.

Recent studies have demonstrated promising results in PD detection using ML and DL models, leveraging features like gait patterns, vocal characteristics, and neuroimaging biomarkers. Challenges include data quality, feature selection, model complexity, interpretability, and clinical validation. Ethical considerations and integration into clinical workflows are also pivotal for widespread adoption. Future research directions aim to refine ML/DL models for early PD detection, validate their performance in clinical settings, and explore transfer learning approaches for optimizing model generalizability. Addressing these challenges will facilitate the development of robust diagnostic tools that improve patient outcomes and quality of life in PD management.

Keywords: *Parkinson disease, Detection, Survey, Machine learning, Deep learning*

1. Introduction

The gradual loss of certain neuron populations is an indicator of neurodegenerative diseases (NDs). Among these conditions, Huntington's, Amyotrophic lateral sclerosis, Parkinson's, and Alzhemier's disease are the most prevalent. Because of their common molecular pathophysiology and variety of clinical manifestations, these disorders provide a serious challenge to physicians [1]. Even while the scientific knowledge of the NDs has advanced significantly, especially in the fields of pathology and pharmacology, it has been difficult to convert preclinical discoveries into successful clinical treatments [2]. The primary emphasis of this research is PD, which typically affect the elderly and linked to a variety of non-motor and motor symptoms [3].

1.1 Parkinson Disease (PD)

PD is one of the most prevalent disease worldwide. World Health Organization (WHO) estimates that 7–10 million people have a PD diagnosis. Women and with PD are around 3:1 in ratio, and PD mostly affects adults older than 50 [4].

PD is the progressive neurological disorder which affect both non-motor and motor symptoms of movement, encompassing functions like planning, starting, and executing movements [5,6]. The symptoms of PD were caused by a significant reduction, typically exceeding 80%, in the number of dopamine-producing cells within Substantia Nigra (SN) of brain [7]. Dopamine collaborates with other neurotransmitter to facilitate communication between muscle cells and nerve, essential for coordinated movement [7]. Insufficient dopamine disrupts this communication, leading to symptoms of PD, like tremors, stiffness, slowed movement, and impaired coordination [8]. Individuals with PD often experience the marked decline in their overall quality of life, participation in social activity, and relationships with family members [9–11]. Causes and risk factors of PD is shown in table 1.1.

Table 1.1. Risk factors and Causes of PD

Causes	Risk Factors
Exact causes are not fully understood.	Age: Risk increases with age, typically appearing after age 60.
Probably a result of a mix of environmental and genetic influences.	Genetics: Family history can increase risk, but most cases are sporadic.
loss of neurons in the substantia nigra, a part of the brain that produces dopamine.	Environmental factors: Toxins such as herbicides and pesticides could be involved.

1.2 Symptoms of PD:

PD symptoms are divided into 2 categories: Non-Motor and Motor symptoms.

1.2.1 Motor symptoms: PD is primarily featured by motor symptoms that result from loss of dopamine-producing neuron in the brain. These symptoms typically worsen over time. The main motor PD symptoms include:

1. **Tremor: A limb, typically the hand or fingers, is where a tremor, or shaking, generally starts. It is typically more pronounced at rest and can lessen by purposeful movements.**
2. **Bradykinesia**: This refers to “slowness of movement”. It can manifest as difficulty initiating movement (akinesia), as well as reduced amplitude and speed of voluntary movements.
3. **Muscle rigidity**: Muscles stiffness, which affects any part of the body. Rigidity can cause pain and limit motion range.
4. **Postural instability**: Impaired coordination and balance, which can lead to difficulties with walking and an increased risk of fall, particularly in later stages of disease.

Other symptoms that can accompany these primary motor symptoms include:

- **Freezing**: Momentary sensations of having one's feet glued to the earth, especially when initiating movement.
- **Micrographia**: A small, cramped handwriting that gets progressively smaller as writing continues.
- **Mask-like expression**: Reduced facial expressions due to stiffness in the facial muscles.
- **Speech changes**: Softening of the voice, monotone speech, or slurred speech.

It's crucial to remember that PD is the complicated disease with symptoms that can vary widely among individuals. Not everyone with PD can experience all symptoms, progression and severity will differ from patient to patient [18].

1.2.2 Non-Motor symptoms:

Other than well-known motor symptoms, PD can also manifest with the variety of non-motor symptoms which can significantly impact quality of life. These symptoms can manifest at any point throughout the disease and, in certain situations, they may even occur before motor symptoms do. Here are some typical PD non-motor symptoms:

1. **Autonomic dysfunction**:
   - **Orthostatic hypotension:** A decrease in blood pressure upon standing that may result in lightheadedness or fainting.
   - **Urinary problems:** Difficulty urinating, urgency, or frequency.
   - **Constipation:** Slowed movement of the digestive tract.
   - **Excessive sweating:** Especially noticeable during sleep.
2. **Sleep disturbances**:
   - **Insomnia:** inability to remain asleep or fall asleep.
   - **REM sleep behavior disorder:** dream acting when you're asleep, which can include violent movements or vocalizations.
   - **Excessive daytime sleepiness:** Feeling very sleepy during the day despite adequate nighttime sleep.
3. **Mood disorders**:
   - **Depression:** Despair, hopelessness, or disinterest in activities that lasts a long time.
   - **Anxiety:** Excessive trepidation, anxiety, or fear.
   - **Apathy**: Lack of motivation or interest in activities.
   - **Irritability**: Easily getting frustrated or annoyed.
4. **Cognitive changes**:
   - **Mild cognitive impairment**: Problems with memory, attention, and other cognitive functions that don't yet meet the criteria for dementia.
   - **Dementia**: Severe cognitive decline that interferes with daily functioning, which can occur in later stages of the disease for some individuals.
5. **Sensory symptoms**:
   - **Loss of sense of smell (hyposmia or anosmia)**: Reduced ability to smell, which can precede motor symptoms.
   - **Pain**: Musculoskeletal pain, often due to rigidity and abnormal posture.
   - **Vision problems**: Blurred vision or difficulty focusing.
6. **Other symptoms**:
   - **Fatigue**: Persistent lack of energy or extreme tiredness.
   - **Sexual dysfunction**: Reduced libido or difficulty achieving arousal.
   - **Skin problems**: Such as excessive oily skin or seborrheic dermatitis.

These non-motor symptoms can vary widely among individuals with PD and may not all occur in every person. They can also fluctuate in severity over time and may be influenced by medications, other medical conditions, or psychological factors. Proper management of PD often involves addressing non-motor and motor symptoms to improve overall quality of life and well-being for patients [19].

1.3 Stages of PD Progression:

PD progresses through five distinct stages, each characterized by different symptoms and levels of impairment. Understanding these stages is crucial for diagnosis, treatment planning, and providing appropriate care and support to patients. Here's an overview of the typical progression of PD:

Stage 1: Mild Symptoms:

- Symptoms are mild and cannot interfere with daily activities.
- Common symptoms like mild tremors, mild movement difficulties, and changes in posture.

Stage 2: Moderate Symptoms:

- Tremors, rigidity, and other movement symptoms become more noticeable and start to affect daily tasks.
- Daily activities may require more effort and individuals may experience fatigue or slowness of movement (bradykinesia).

Stage 3: Balance and Coordination Issues:

- Balance and coordination are noticeably impaired.
- Falls become more common due to instability.
- Despite these challenges, many individuals can still live independently with assistance.

Stage 4: Severe Symptoms:

- Symptoms are severe and debilitating.
- Individuals may require help with daily activities and may not be able to live alone.
- Walking may still be possible, but it is often difficult and requires significant assistance.

Stage 5: Advanced Parkinson's Disease:

- This stage is characterized by a significant decline in mobility and independence.
- Many patients are wheelchair-bound or bedridden.
- Cognitive decline and hallucinations/delusions may occur.
- Patients require full-time care and support.

Diagnosing PD involves recognizing non-motor and motor symptoms.

1.4 Impact on Quality of Life:

PD not only affect physical abilities but also has a profound impact on emotional well-being, social interactions, and overall quality of life. As disease worsens, People find it harder and harder to be independent and participate in the things they like.

1.5 Risk of Other Chronic Diseases:

PD patients have, increased risk of developing other chronic diseases, like cardiovascular disease, osteoporosis, and urinary problems. Managing these comorbidities is essential for overall health and well-being [20].

1.6 Need for Early detection of PD:

Understanding PD stages is crucial for healthcare providers and caregivers to provide appropriate care and support throughout the disease progression. Early Detection of symptoms and timely intervention can help improve life quality and delay disability for individuals with PD. It can be difficult to distinguish PD from other neurological conditions with comparable etiologies, especially since 75% of PD patients are idiopathic. Computerized methods based on ML and DL are becoming more and more necessary to improve diagnosis accuracy and help physicians make wise decisions [21]. These methods may enhance diagnostic performance in PD and associated disorders.

2. Literature review:

Machine learning (ML) techniques are rapidly being explored for early detection and diagnosis of PD. Machine Learning Techniques for PD Detection:

1. Supervised Learning:
   - Classification Models: Trained on labeled data (PD vs. non-PD) from clinical assessments, imaging, or genetic profiles to predict PD status in new cases.
   - Example Algorithms: Logistic Regression, Random Forest, Support Vector Machines (SVM).
2. Unsupervised Learning:
   - Clustering Models: Identify patterns or subgroups within PD patients based on symptom severity, genetic profiles, or response to treatment.
   - Example Algorithms: K-means clustering, Hierarchical clustering.
3. Deep Learning:
   - Neural Networks: Utilized for complex data such as image recognition in MRI/PET scans or time-series analysis of movement data.
   - Convolutional Neural Networks (CNNs): MRI and PET Analysis: CNNs can analyze brain images to detect structural abnormalities or changes in metabolic activity associated with PD. Feature Extraction: Extract relevant features from imaging data to identify subtle patterns indicative of PD.
   - Recurrent Neural Networks (RNNs): Suitable for analyzing sequential data from wearable sensors to detect motor symptoms like tremors or fluctuations in movement patterns.
   - Hybrid Architectures: Combination of CNNs and RNNs: Integrating CNNs for image analysis (e.g., brain scans) with RNNs for temporal analysis (e.g., movement data) to provide a comprehensive assessment of PD.

2.1 Related works for PD detection using ML:

A study referenced by [22] explored various methods to classify vocal symptoms as potential indicators of Parkinson's Disease (PD). The study encompassed data collection, extraction, and selection processes. Eleven classification methods were compared based on performance metrics such as F1 scores, ROC curves, MAE, and recall. Using a MAFT (machine learning methodology), the study evaluated the effectiveness of 11 distinct classifier techniques. Results indicated that the HM achieved the highest diagnostic accuracy, achieving an impressive rate of 96.6%. After filtering the dataset, both HM and NB algorithms showed significant improvement in accuracy, with an increase of up to 3%. While offering valuable insights for future research, the study noted limitations such as the exclusion of runtime periods and computational effort from the evaluation. Future investigations aim to prioritize examining diverse medical scenarios and benchmark datasets to validate the strategy's efficacy.

In their study, [23] employed lightweight deep learning (PLDL) techniques with dual training to effectively identify patterns in hand drawings from PD patients and healthy persons. The system's extensive procedure includes image pre-processing, data augmentation, deep feature selection with a 50% failure rate, and binary classification as final steps. The findings suggest that waveform analysis could be a valuable approach for PD detection, particularly when utilizing the LDLS method and considering both individual and aggregate MobileNet features to enhance identification accuracy. The study achieved a perfect detection rate of 100% using the KNN classifier and its inherent characteristics.

In another study referenced as [24], human gait signals were analyzed for classifying individuals with Parkinson's disease using feature extraction techniques employing local binary pattern algorithms. The study introduced “Local Gradient Pattern (LNGP), Local Neighbor Description Pattern (LNDP), Local Gradient Pattern (LGP)” as enhancements to traditional Local Binary Pattern (LBP) for extracting feature’s from gait data. After data retrieval

and statistical analysis, the Kruskal-Wallis test is employed to determine the most relevant attributes, followed by classification using Artificial Neural Network (ANNs). SWLNGP approach achieved impressive accuracy rate 96.28%, outperforming existing methods. These findings strongly support the efficacy of SWLNGP in identifying characteristic gait patterns associated with Parkinson's disease.

The authors of [25] evaluated machine learning techniques that utilize voice noise assessment and multiple features assessment (MFEA) within the multi-agent system to enhance accuracy of PD diagnosis. They conducted diagnoses before and after analyzing voice disturbances using five different classification schemes: SVM, Random Forest, Neural network, Naïve bayes, Decision tree. The evaluation employed 10 fold cross validation to gauge the algorithms' learning capabilities and monitor their performance consistency. MFEA was employed to identify the optimal feature set for the multi-agent system, aiming to improve the classifiers' overall performance.

Another study by [26] employed neural network classification, decision tree, and Naïve Bayes techniques for diagnosing Parkinson's disease. By independently applying these three classification methods to a dataset featuring characteristics indicative of voice disorders in humans, the researcher successfully addressed the problem. Evaluation of the methods revealed, decision tree achieved 91.63% accuracy, while neural network performed slightly lower at 89.46%. These findings suggest that employing a decision tree supplemented by Naïve Bayes is advisable to dataset's sharing similar attributes.

Another study utilized time frequency feature's of audio data to evaluate a ML system comprising the "stacked autoencoder and the KNN" algorithm. When applied to PD detection using Istanbul and Oxford datasets, approach achieved accuracy rates ranging from 94-98% [27].

Another study [28], researchers proposed employing Light Gradient Boosting and Extreme GB algorithms to differentiate PD using 256 auditory features collected from 40 healthy and 40 PD patients. Additionally, feature analysis methods were employed to identify the seven most relevant features. The classification accuracy achieved with these seven features was approximately 82%.

Furthermore, a different study [29] demonstrated the potential of the backpropagation with variable adaptive momentum (BPVAM) method for identifying Parkinson's disease by audio data from 8 healthy, 23 PD cases. Prior to classification, principal component analysis (PCA) is applied to the audio data to extract optimal features. The study achieved an accuracy of 97.5% by leveraging the 15 most discriminative features. However, the process of speech categorization took approximately seven seconds longer when employing PCA and BPVAM on a CPU workstation.

In addition, another investigation [30] employed a combination of ML techniques, like SVM, Random Forest, logistic regression, light generalized based on statistics (GBS), and a stacked ensemble model, to distinguish motor discrepancies detected by wearable sensors between PD and other neurological conditions. The study tested two sets of features: one consisting solely of tremor features and another combining tremor with bradykinesia features. The utilization of both feature sets yielded the highest accuracy rate of 85%. Conversely, accuracy dropped to 80% when the machine learning models were trained solely on jitter characteristics.

[31] conducted a study suggesting that Parkinson's disease (PD) could potentially be identified using DTI MRI along with binary support vector machines (SVM) and multi-kernel learning (MKL) architectures. Their methodology involved preprocessing a DTI MRI dataset containing 57 controls and 162 PD subjects to analyze clinical diffusion metrics and additional distribution metrics. MKL was employed across various sets of diffusion metrics, and each of the identified five diffusion measures underwent SVM analysis. The study found that, "area under the receiver operating characteristic curve (AUC-ROC)" did not exceed 60%. Consequently, the researchers concluded that DTI-based assessments may often be inadequate for accurate classification of PD patients. Table 2.1. specifies the Summary of related works on early PD detection using ML methods.

Table 2.1. Summary of related works on early PD detection using ML methods

Ref.	Objective	Dataset (Data type)	Algorithm	Result/Accuracy
[22]	PD Diagnosis	Private dataset (vocal symptoms)	CN2 , KNN, RF, DT, LR, AdaBoost, SGD, SVM, NN, NB, HM	78.5%, 85.6%, 87.2%, 85.1%, 86.2%, 86.2%, 86.7%, 88.2%, 91.3%, 81.5% 96.9%

[23]	Improve PD detection accuracy	Kaggle Dataset [44] (Hand-Sketchs for 51 healthy and 51 PD)	MobileNet-KNN	100%
[24]	Recognition of PD Based on Gait Signals	PhysioNet (Private dataset) Gaitpdb Walking signals for 166 people	SWLNGP SWLBP LNGP LBP LNDP SWLNDP LGP ANN	95.08% 95.50% 94.43% 93.83% 92.38% 93.50% 94.42% 96.28%
[25]	Improving the diagnosis of PD	Private Dataset (Human voice recording)	SVM, Naïve Bayes, Random Forest, Neural Network, and Decision Tree	86.440% 74.111% 87.755% 86.734% 86.294%
[26]	Evaluation of classification methods PD	Private Dataset (Human voice recording for 31 people, 23 diagnosed with PD). Collected using Intel At-Home Testing Device (AHTD) at the home of volunteered Patients [45]	Decision Tree Naïve Bayes Neural Network	91.63% 89.46% 91.01%
[27]	Detection of PD	Speech Data (Istanbul:20 healthy and 20 PD patients) and (Oxford:8 healthy and 23 PD patients)	KNN, stacked autoencoder	98% 94%
[28]	Detection of PD	UCI Machine Learning Repository “Parkinson Dataset with Replicated Acoustic Features Data Set” (Information on the speech of 40 healthy and 40 PD patients)	GB, Extreme GB	82%
[29]	Detection of PD	Oxford Parkinson’s Disease Detection Dataset (8 healthy and 23 PD patients voice recordings) [46]	BPVAM	97.5%
[30]	PD in Comparison to Neurological Conditions	Private Dataset (Data collected using SensorTile device from 56 patients' senses)	Random Forest, Stacked Ensemble Model, Light GBM, and SVM	85% accuracy
[31]	Detection of PD	DTI datasets, Parkinson’s Progression Marker Initiative (PPMI) database [47]. (Included 162 individuals with PD and 70 control subjects who underwent DTI MRI scans)	bSVM MKL	58% 60%

2.2 Related works for PD detection using DL:

[32] employed a DL technique known as Convolutional Neural Networks (CNN) to classify patient's with PD and healthy individuals. The input data was weighted by parameters, and the structural connectome matrices, varying with the number of streamlines from diffusion MRI (dMRI), were evaluated with high accuracy through training. Additionally, they utilized gradient-weighted class activation mapping (Grad-CAM) to visualize crucial regions of the connectome matrices, which played a significant role in CNN's decision-making process.

[33] employed a deep learning (DL) system, specifically a CNN, best suitable for image classification, to analyze SPECT images of healthy individuals and PD patients. Once trained, the CNN effectively distinguishes between non-PD and PD cases based on these images. In contrast to traditional human interpretation methods of FP-CIT-SPECT imaging, DL model mitigates the variability inherent in human assessments and offers a more objective classification of patient groups. This system is particularly valuable for patients with ambiguous Parkinsonism and for classifying a typical subgroup such as SWEDD.

[34] utilized two classifiers along with various techniques for classification and feature selection to achieve high accuracy. K-nearest neighbor (kNN) proved most effective for clinical staging and classification of PD motor symptoms. Adjusting the hyperparameter k can enhance its classification accuracy. On the other hand, SVM, identifies an optimal hyperplane to separate different class data points with maximum margin, making it suitable for high-dimensional and noisy data. However, SVM's performance was sensitive to the choice of hyperparameters and kernel functions. Consequently, it performed best in classifying dementia status.

[35] employed a combination of Random Forest (RA) and Artificial Neural Network (ANN) techniques to probabilistically detect disease. They utilized RA for data preprocessing, handling patient vocal recognition, iron content, and pulse rate data. Subsequently, the preprocessed data was inputted into a trained ANN. Resultant probability value's and 5 attribute outcomes from RA were stored in the file for calculating the probability of PD using ANN. Achieved 95.64% sensitivity, 67.34% specificity and 93.46% accuracy, which they compared favorably against other methodologies. Their algorithm was implemented using the C language and the SCILAB program for graphical representation.

[36] introduced a method combining CNN and ANN architectures for analyzing MRI and SPECT scans. Their approach involved preprocessing the MRI data through techniques such as image resizing, augmentation, normalization, and noise reduction. Subsequently, the preprocessed MRI data were fed into a pre-trained CNN model. For the SPECT dataset, they employed different preprocessing techniques: "data cleaning instead of image resizing and feature selection instead of noise removal". ANN model was then trained using the preprocessed SPECT data.

[37] utilized T2-weighted brain MRI to detect PD using the pretrained CNN named AlexNet. AlexNet incorporates various layers such as input, convolutional, pooling, dropout, fully-connected layers, enabling it to classify inputs as healthy/PD through essential operations. Performance of the pretrained AlexNet was evaluated based on accuracy, specificity, and sensitivity. The authors achieved the specificity 88.4%, 89.3% sensitivity, 88.9% Accuracy with the proposed approach, comparing favorably with other methods.

[38] employed a computer vision method to enhance PD detection. They utilized HoG(histogram of oriented gradients) to extract features and implemented a CNN on a sequential model for the lightweight architecture. Achieved an impressive accuracy of 94%, with sensitivity and specificity rates of 80% and 92%, respectively. Model is suitable for deployment on embedded and handheld devices, facilitating rapid self-analysis.

[39] recommended the computer-based analysis algorithm utilizing CNN to generate diagnostic biomarkers, termed NeuroMelanin-sensitive MRI (NMS-MRI), for Parkinson's Disease (PD). They implemented a standard CNN architecture based on ResNet, renowned for its efficacy in medical image classification. In their study, they conducted comparisons with the RA(Regression Analysis) CR-ML(Contrast Ratio Classifier), demonstrating superior accuracy, sensitivity, and specificity with their proposed method. Their novel approach achieved an accuracy of 83.6% in cross-validation, surpassing the 81.8% accuracy attained by RA and outperforming conventional radiomics techniques.

[40] utilized CNNs to analyze brain MRI images for detecting Parkinson's disease (PD). They chose this model due to its spatial awareness, which helped reduce the number of hyperparameters. Their architecture consisted of five convolutional layers, each employing ReLU activation. The first layer had 16 filters, the second had 32, and the subsequent layers had 64 filters each. The model also included 5 max-pooling and the flattening layers

positioned between first dense layer and last pooling layer. Additionally, ReLU activation is applied to 128 primary layers, while SoftMax activation was used at the final two layers, totaling 130 dense layer's. Achieved an accuracy of 95%, with sensitivity and sensitivity approaching 97%.

[41] employed "Deep Neural Network (DNN)-based CNN and CNN-RNN" architectures to diagnosis PD. They utilized the ResNet50 (Residual Network-50) to convolutional and pooling layers. In CNN-RNN model, GRU (Gated Recurrent Units) were incorporated in RNN component. Initially, CNN-RNN is trained using MRI dataset, achieving approximately 70.6% accuracy on test set. Subsequently, performance is improved by modifying Loss Function. CNN model, consisting of two fully connected layers without hidden layers, achieved approximately 94% accuracy. On the other hand, CNN-RNN, featuring the 2 hidden and one fully connected layer, achieved approximately 98% accuracy.

[42] employed the LeNet-5 architecture to detect PD at initial stage, leveraging its CNN structure. The model contains 2 Conv2D layers, 2 pooling layers, and the hidden layer. The baseline configuration includes two dense layers: ReLU activation with 128 neurons is used in the first layer, whereas sigmoid activation with two neurons per layer is used in the second layer.
Using the batch size of 32 across 30 epochs, trained the model. The model obtained roughly 97.6% accuracy on test set, and 96.6% accuracy on train set with 0.07% as the loss, without batch normalization. Incorporating batch normalization slightly altered these results: the training dataset accuracy decreased to 95.4%, while the testing dataset accuracy improved to 97.9%, with a reduced loss of 0.05%.

[43] utilized a customized version of the Visual Geometry Group (VGG) Net architecture, a CNN, for PD detection. Among four architectures compared, their modified VGG Net architecture demonstrated the highest accuracy. This architecture comprises multiple blocks, each featuring 2D convolutions. They inputted the swallow tail sign extracted from brain MRI scans into this model. Originally designed to recognize about 1000 object categories such as keyboards, people, animals, and more, the VGG Net model achieved an impressive efficiency of approximately 93% in PD detection. Table 2.2. Summary of related works on early PD detection using DL methods.

Table 2.2. Summary of related works on early PD detection using DL methods

Ref.	Objective	Dataset (Data type)	Algorithm	Result
[32]	To differentiate PD patients from hezavlthy people	MAGNETOM Prisma; Siemens Healthcare (MRI images from 3-T MRI unit)	CNN	Accuracy: 67%to89%
[33]	Diagnosis of PD via DAT imaging interpretition	PPMI database [47] and SNUH cohort. (SPECT images)	CNN	Improved performance in image classification: DAT(98%)
[34]	Early Diagnose of PD	Private Dataset (Brain MRI images)	KNN, SVM	Using several datasets, the accuracy of 99.53, 99.22, and 98.70% is achieved.
[35]	Efficient detection of PD	PPMI Dataset [47] (Motor and Non-motor symptoms)	RA, ANN	93.46% accuracy
[36]	Early prediction of PD	PPMI Dataset [47] (MRI, SPECT scans)	CNN, ANN	Suggested the use of CNN as a more dependable

				technique for PD detection
[37]	Diagnosis of PD	Private Dataset (Collected Brain MRI using 3T Scanner)	AlexNet	Accuracy: 88.9%
[38]	PD Detection	PPMI Dataset [47] (SPECT)	Computer vision, HoG, CNN	Accuracy: 94%
[39]	PD diagnostic biomarkers	Private Dataset (NMS-MRI (NeuroMelanin-sensitive))	CNN+ResNet	Achieved 80% test accuracy in comparison to the 60% accuracy of the RA-ML (Radiomics-based classifier).
[40]	To precisely diagnose PD	PPMI Dataset [47] (Brain MRI)	CNN	Accuracy: 95%
[41]	PD Detection	Private Dataset [48] (MRI, DaTScan Data)	CNN-RNN	Accuracy: 98%
[42]	Early Detection of PD	PPMI Dataset [47] (MRI)	LeNet-5	Accuracy: 97.63%
[43]	Early Detection of PD	PPMI Dataset [47] (Brain MRI)	VGG, CNN	93% accuracy

3. Challenges and Issues identified from existing related works for PD detection:

Detecting PD with DL and ML introduces specific challenges and issues, which include:

3.1 Data Quality and Quantity: Obtaining sufficient high-quality data is crucial to train ML/DL models accurately. Data may be sparse, noisy, or unbalanced (with fewer positive cases of Parkinson's disease), which can affect the model's performance and generalizability.

3.2 Feature Representation: Choosing or extracting appropriate features from raw data (such as voice recordings, gait patterns, or imaging data) is challenging. Deep learning models can potentially learn relevant features automatically, but this requires large amounts of labeled data and careful preprocessing.

3.3 Complexity of Models: DL models like RNNs, and CNNs, are powerful but complex. Training deep models requires substantial computational resources and proficiency in adjusting hyperparameters to get the best results.

3.4 Interpretability: Since DL models are sometimes seen as "black boxes," it might be challenging to comprehend how they make their predictions. In medical applications like PD detection, interpretability is crucial for clinicians to trust and use model effectively.

3.5 Transferability and Generalization: Ensuring that deep learning models generalize well to new patients or populations is challenging. Models trained on particular datasets may not perform accurately on data from different demographics or with variations in disease progression.

3.6 Ethical and Privacy Concerns: Deep learning models trained on medical data raise ethical concerns regarding patient privacy, data usage, and potential biases in data that could disproportionately affect certain groups.

3.7 Validation and Clinical Adoption: Validating deep learning models in clinical settings is essential to demonstrate their reliability and effectiveness compared to existing diagnostic methods. Clinicians may be hesitant to adopt new technologies without robust validation and evidence of clinical utility.

3.8 Integration with Clinical Workflow: Integrating machine learning or deep learning models into clinical practice requires smooth interaction with current electronic health records (EHRs) and diagnostic procedures. Models should provide actionable insights that improve patient care without disrupting clinical routines.

Addressing these challenges requires collaboration between machine learning researchers, clinicians, and domain experts in Parkinson's disease. Robust data collection, careful model development, rigorous validation, and considerations for ethics and interpretability are essential to develop effective and clinically applicable detection tools using machine learning and deep learning.

4. Research Objectives

- **Early Detection**: Develop ML and DL models capable of accurate PD detection at early stages based on clinical data, genetic profiles, imaging results, and other biomarkers. Objective measures could include improving accuracy, sensitivity and specificity compared to other detection methods.
- **Technology Integration and Validation**: Validate ML and DL models in real-world clinical settings to assess their reliability, generalizability, and impact on patient care. This involves integrating these technologies into existing Clinical workflows, electronic health records (EHRs), and healthcare systems.
- **Transfer Learning**: Explore transfer learning techniques in ML/DL to adapt models trained on larger datasets or other neurological disorders for PD-related tasks, optimizing model performance with limited PD-specific data.

5. Conclusion

Degeneration of dopamine-producing neurons in Substantia Nigra area of the brain is the characteristic of PD, a neurological disorder that progresses over time. This neuronal loss leads to the range of non-motor and motor symptoms that significantly impact patients' quality of life.

PD motor symptoms include tremors, postural instability, muscle rigidity, bradykinesia. These symptoms worsen over time which can lead to difficulties with daily activities such as walking, writing, and speaking. Non-motor symptoms are diverse and include sleep disturbances, autonomic dysfunction, mood disorders, cognitive changes, sensory symptoms, and others like fatigue and sexual dysfunction.

PD progresses through stages from mild to severe, impacting patients differently in terms of symptoms and functional abilities. Early detection, appropriate diagnosis were crucial for implementing timely interventions to manage symptoms and improve outcomes.

Recent advancements in medical research, particularly in the fields of ML and DL, have shown promise in enhancing PD diagnosis and treatment. ML techniques such as unsupervised learning (like clustering) and supervised learning (like Random Forest, SVM) and are used to analyze clinical data, genetic profiles, and imaging results to predict and classify PD. DL models like CNN and RNN are used to analyze complex datasets such as MRI scans and voice recordings, aiming to improve diagnostic accuracy and identify early biomarkers of PD.

Challenges in applying ML and DL to PD include ensuring the quality and quantity of data, selecting relevant features from complex datasets, managing the complexity of models, and addressing issues of interpretability and generalization. Ethical considerations around patient privacy, data usage, and potential biases in medical data also require careful attention.

Clinical adoption of ML and DL technologies for PD diagnosis requires rigorous validation in real-world settings to demonstrate reliability and effectiveness compared to traditional diagnostic methods. Integration into clinical workflows and electronic health records (EHRs) is essential to facilitate seamless implementation and enhance patient care.

In conclusion, leveraging ML and DL holds significant potential to advance PD research by enabling earlier detection, personalized treatment strategies, and improved management of both non-motor and motor symptoms. These technologies aim to enhance overall patient outcomes, prolong independence, and eventually enhance the standard of living for Parkinson's disease patients.

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