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# Recognition of Parkinson’s Disease Using Artificial Intelligence: A Review

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***Abstract —*** *The paper contains a detailed review of a variety of deep learning and machine learning-based approaches and other strategies also used to diagnose Parkinson’s disease (PD) and their impact on opening up new study possibilities. From previous research, we can see a lot of deep learning and AI-based techniques are defined to detect signs based on different symptoms and datasets, similarly a kind of algorithms were used for the diagnosis of PD. Using these technologies, many data can be handled and a solid statistical prediction can be made, so these techniques are getting more practical.*
***Keywords—*** *Parkinson’s Disease (PD), Deep Learning, Machine learning, Artificial intelligence.*

## I. INTRODUCTION

Parkinson’s disease is a very common disease of the nervous system, that usually manifests itself in adults over the age of 50 [1-23], and PD is an illness of the nerve system that affects body mobility. It’s a long-term and progressive illness. UPDRS is an acronym that stands for "Unified Parkinson's Disease Rating Scale." is a rating tool that is the primary method used in clinics for the detection of PD [1]. It is an example of neurodegenerative disease that occurs when nerve cells in the brain gradually lose function and eventually die. In our aging culture, neurodegenerative illness is one of the most serious health issues [2]. It primarily affects the body's motor system that supports motor functions in the nervous system with the increase in illness or with time, it generates non-motor symptoms. PD diagnosis based on speech signals as voice disorder (Dysphonia) is a significant symptom of PD [3,4]. The problem of PD patients has increased in this COVID-19 pandemic situation because people are unable to take more care [5]. A lot of deep learning, machine learning, and AI-based techniques are defined for the detection of symptoms [6]. Recently rather than these techniques various kinds of sensors have been used as a diagnostic tool for the diagnosis of symptoms of Parkinson’s disease [7]. As the condition becomes worsens over time early detection is needed recently speech changes in Parkinson’s disease patients use to detect the symptoms. Recent Parkinson's disease telemedicine investigations focused on vocal disorders-based systems, with machine learning classifiers from Dysphonia, a voice condition, being applied to Parkinson's disease [8-11]. Parkinson’s disease patients’ handwriting also degrades with time so it can also be used for the diagnosis of the disease [12]. Machine learning model based on the MR images of PD patients also gives good accuracy by creating a brain heat map [13]. Artificial Intelligence (AI) techniques have recently gotten a lot of medical attention because these technologies can handle a lot of data and make strong statistical predictions [14]. In 1817, an English physician named James Parkinson was the first to describe that around 10 million people worldwide are affected with Parkinson's disease each year. [15].

Based on the mobility of a person’s body, signs of Parkinson’s disease can be categorized into two types-
**Motor Symptoms:** Symptoms related to the movement of the body known as motor symptoms. The four major impairments are tremor, stiffness, bradykinesia, and postural instability.

**Non-motor Symptoms:** Symptoms which have nothing to do with physical movement are called non-motor symptoms; fatigue, hypotension, restless Legs, dementia, depression, pain, eye problem, foot care, mouth and dental issue, speech and communication problems are some common symptoms of this. [1-23]


**Fig 1:** Parkinson's disease causes major symptoms

These symptoms may vary from one individual to another; It is a progressive disease so the condition becomes more worsens with time. The Hoehn and Yahr Scale (HY) is used to group symptoms of Parkinson's disease into five stages; mildest stage after this stage changes in movement and posture are also noticeable in the next stage symptoms begin to obstruct your regular activities in next stage assistance is required to carry out daily tasks and in the last stage the patients are completely confined to their beds [16].

## II. LITERATURE REVIEW

**Table1:** Summarizes the diagnosis of Parkinson's disease based on physiological markers.

| Author | Dataset | Subjects | Approach | Accuracy(%) |
|---|---|---|---|---|
| Shahid A.H. et. al. [1] | Telemonitoring dataset | 42 (28 men,14 women) | Principle component analysis based DNN model | * |
| Kaur S. et. al. [2] | (i) Speech Dataset (ii) Diabetes Dataset (iii) Breast Cancer Dataset (iv)Telemonitoring dataset | (i) 196 (by 31 individual, 23 impaired by PD) (ii) 768 females (iii) 699 females (iv)188(107 men,81women) | Optimized deep learning model for classification, Grid search optimization | 91.69 |
| Valdovinos et. al [3] | * | * | Uses decentralized approach | * |
| YANHAO XIONG et. al. [4] | Speech Dataset | 188(107 men,81 women) | Support Vector Machines(SVM),Logistic Regression(LR),Naive Bayes(NB),Gradient Boosting Model(GBM),Random Forest(RF),Linear Discriminant Analysis(LDA), Adaptive WSO Algorithm,Sparse Autoencoder Neural Network. | SVM 85 ,LR 87, NB 82,GBM 88, RF 81,LDA 95 |
| Zahid Laiba et. al. [5] | Speech Dataset | 50(25 men,25 women) | Transfer Learning, Random Forest, Multilayer Perceptron | TL 72,MP 99.7,RF 99 |
| M. Jyotiyana et. al. [6] | Speech Dataset | 42 | Deep Neural Network-based classification model | 94.87 |
| C. Quan et. al. [8] | Speech Signals | 45(25 men,20 women) | Bidirectional LSTM model using dynamic speech features and the end-to-end DL using CNN model | * |
| O.Asmae et. al. [9] | Vocal Phonations | 31 | ANN classification ,KNN classification | 96.7 |

| | | | | |
|---|---|---|---|---|
| Sohail Esmaeilzadeh et. al. [13] | MRI Dataset | 452(292 men,160 women) | Convolutional Neural Network Model | 100 |
| Ball, Nicole et. al. [15] | * | * | By studying how environmental variables interact with and impact the brain, we can discover PD's underlying cause(s). | * |
| A. H. Butt et. al. [21] | * | 114(79 men,35 women) | Bi-direction Long ShortTerm Neural Network (BLSTM) | 82.4 |
| Filippo Cavalloa et. al. [22] | * | 90(71 men,19 women) | SVM,RF,NB | RF 95,SVM 97 |
| Saha Roshni et. al. [23] | MRI Dataset | 54 | Convolutional Neural Network Model | 97.63(without batch normalization),97.91(with batch normalization) |
| S. Raval et. al. [24] | Tappy ,handwriting and Speech dataset | Tappy ,handwriting and Speech dataset | Random Forest Classifier (RF), Adaptive Boosting (AB) and Hard Voting (HV) | 99.79 |
| Taoufiq BELHOUSSINE DRISSI [25] | Speech Dataset | 18 healthy and 20 PD patients | Wavelet transform transformation, extraction of MFCC from the signals,SVM classifiers | 86.84 |

**Table2:** Prediction ,Monitoring and classification of Parkinson's disease using voice factors.

| Research | Work Proposal | Classified | Signal Analysis | Acc. |
|---|---|---|---|---|
| Lahmiri and Shmuel [26] | Access the performance of FS techniques | RSVM | (FS) t-test, entropy, Bhattacharyya statistic, ROC, Wilcoxon Statistic, FMI, GA, RFE-CBR | Acc-Wilcoxon based (92.21%), Se-ROC based (99.63%), Sp-ROC based (82.79%) |
| Sharma et al. [27] | Modified Gray Wolf Optimization (MGWO) as a search strategy for FS | KNN, RF, DT | (FS) MGWO | outperformed OCFA with Acc-94.83%, DR-98.28%, FAR-16.03% |
| Kadam and Jadhav [28] | Proposed feature ensemble based SAE | DNN (SoftMax Regression) | (FE) SAE | outperforms DNN with Acc-92.19%, Se-97.28%, Sp-90% |
| Shukla et al. [29] | Proposed Multiple Pre-Processing technique for early detection of PD | J48, NB, SVM, RF, KNN, MLP, DT, NB Tree | (Pre-P) Discretization, (FS) CFS, ReliefF, IG, CS, PCA | Best-RF, Acc-94.98%, Se-93.18%, F1-94.7%, P-94.96% |
| Almeida et al. [30] | Evaluation of various feature extractors and classifiers | KNN, MLP, OPF, SVM | (Pre-P) Separate voiced and unvoiced parts, (FE) 18 different feature sets, (FS) t-SNE, (PP) N-way ANOVA, Friedman/Kruskal–Wallis, Nemeyi | AC channel-Acc-94.55%, AUC-0.87, EER-19.01%, SP channel-Acc-92.94%, AUC-0.92, EER-14.15% |
| Moro-Velázquez et al. [31] | Influence of kinetic changes for automatic PD diagnosis | GMM-UBM (Reynolds et al., 2000), i-vector-GPLDA (Dehak et al., 2010) | (Pre-P) Filtering, Downsampling (16 KHz), Normalization, Hamming windowing (10-40 ms), (FE) PLP, MFCC, LPC, (PP) RASTA for PLP | Acc-87%, AUC-0.93 |
| Tuncer and Dogan [32] | Eight-pooling Octopus based FE network | SVM (Linear, RBF, Cubic), KNN, LR, DT | (Pre-P) Octopus method-minimum, maximum, range, average, variance, median, kurtosis and skewness, (FE) SVD, (FS) NCA, (PP) Mode based | Acc-99.21% (Gender), 98.4% (PD), 97.62% (PD & Gender) |
| Zhang [32] | Potential of smartphones in low-cost PD diagnosis | KELM, SVM (MultiLayer, Linear, RBF), CART, KNN, LDA, NB | (FE) SAE | Acc-94%–98% |

**Table3:** Using deep learning algorithms, table summarizes the diagnosis of Parkinson's disease.

| Research | Dataset | Subjects | Classifier | Performance | | |
|---|---|---|---|---|---|---|
| | | | | Specificity | Accuracy | Sensitivity |
| Frid A et. al.[34] | Speech dataset | 43-PD 9-HC | CNN | * | 83.63% | * |
| | | | | | | |
| Oh SL et. al.[35] | EEG dataset | 20-PD 20-HC | CNN | 91.70% | 88.25% | 84.71% |
| | | | | | | |
| Zhao A et. al.[36] | Gait dataset | 93-PD 73-HC | LSTM&CNN | * | 97.48% | * |
| | | | | | | |
| Caliskan A et. al.[37] | Speech dataset (OPD&PSD) | 23-PD 8-HC | DNN | * | Mean AR-93.79% | * |
| | | 20-PD,20-HC | | | Mean AR-68.05% | |
| Gunduz H et. al.[38] | Speech dataset | 188-PD 64-HC | CNN | * | 84.50% | * |
| | | | | | | |
| Al-Fatlawi AH et. al.[39] | Speech dataset | 23-PD 8-HC | DBN | * | 94.00% | * |
| | | | | | | |
| Wodzinski M et. al.[40] | Speech dataset | * | ResNet | * | 90.00% | * |
| | | | | | | |
| Dai Y et. al.[41] | PET dataset | 214-PD 127-HC | U-Net | * | 84.00% | * |
| | | | | | | |
| Alharthi AS et.al.[42] | Gait dataset | 93-PD 76-HC | LSTM & CNN-2D | * | 96.00% | * |
| | | | | | | |
| Pahuja G et.al [43] | (SBR values+5 Biomarkers) | 384-PD 148-HC | CNN and MLR | * | 99.62% | * |
| | | | | | | |
| Gil-Martín M et.al.[44] | Spiral drawing dataset | 62-PD 15-HC | CNN | * | 96.50% | * |
| | | | | | | |
| Banerjee M et.al.[45] | dMRI dataset | 44-PD 50-HC | CNN | * | 88.88% | * |

**Table 4:** Using machine learning techniques, table summarizes the diagnosis of Parkinson's disease using neuroimaging techniques.

| References | Dataset | Subjects | Approach | Classifier | Performance | | |
|---|---|---|---|---|---|---|---|
| | | | | | Specificity | Accuracy | Sensitivity |
| Sharma P[46] | fMRI dataset | 510-PD,760-HC | PCA | LS-SVM | * | 87.89% | * |
| Georgiopoulos C[48] | fMRI dataset | 20-PD,20-HC | ICA | GLM | * | * | * |
| Abós A[50] | fMRI with MCI | 70-PD,38-HC | Randomized Logistic Regreesion | SVM | * | 82.60% | * |
| Rubbert C[51] | rs-fMRI dataset | 42-PD,47-HC | * | Boosted Logistic Regression | 72.70% | 76.20% | 81% |
| Chen Y[54] | rs-fMRI dataset | 26-PD,26-HC | Kendall Tau correlation cosfficient | SVM | 90.47% | 93.62% | 96.15% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Kazemineja d A[56] | rs-fMRI dataset | 19-PD,18-HC | AAL atlas | SVM | * | 95.00% | * |
| Sateesh Babu G[49] | MRI dataset | 127-PD,112-HC | RFE | PBL-McRBFN | 81.00% | 82.32% | 83.47% |
| Peng B[47] | MRI dataset | 69-PD,103-HC | Wrapper feature selection method | Multi Kernel SVM | 87.79% | 85.78% | 87.64% |
| Rana B[52] | MRI dataset | 30-PD,30-HC | VBM, mRMR | SVM | * | 88.30% | * |
| Zhang L[53] | MRI dataset | 16-PD,16-HC | PCA | SVM | * | 93.75% | * |
| Zeng LL[55] | MRI dataset | 374-PD,169-HC | Joint Feature Sample Selection(JFSS) | LDA | * | 81.90% | * |
| Zeng LL[69] | MRI dataset | 45-PD,40-HC | * | SVM | * | 95.00% | * |

## III. CONCLUSION

This assessment looked at a number of papers based on machine learning and deep learning techniques for detecting Parkinson's disease (PD). Deep learning models are now having a significant impact in the field of health care. To achieve high accuracy in the diagnosis of Parkinson's disease, deep learning models should be supplemented. Several machine learning and deep learning algorithms can be quite well as a result of this survey.

## REFERENCES


[1]. Shahid A.H.,Singh M.P. A deep learning approach for prediction of Parkinson's disease progression.Biomed.Eng.Lett 10,227-239(2020).

[2]. Kaur S.,Aggarwal,H.&Rani,R.Hyperparameter optimization pof deep learning model for prediction of Parkinson's disease.Machine Vision and Application 31,32(2020).

[3]. Valdovinos, B.Y., Modica, J.S. & Schneider, R.B. Moving Forward from the COVID-19 Pandemic: Needed Changes in Movement Disorder Care and Research. Curr Neurol Neurosci Rep(2022).

[4]. Xiong, Y. and Lu, Y., 2020. Deep feature extraction from the vocal vectors using sparse autoencoders for Parkinson's classification. IEEE Access, 8, pp.27821-27830.

[5]. L. Zahid Et Al., "A Spectrogram-based Deep Feature Assisted Computer-Aided Diagnostic System for Parkinson;'s Disease,"in IEEE Access, Vol. 8, pp. 35482-35495,2020.

[6]. Jyotiyana, M, Kesswani, N.,& Kumar, M.(2021). A deep learning approach for classification and diagnosis of Parkinson's disease.

[7]. R. Torres,M.Huerta,R.Gonzalez,R Clotet,J.Bermeo and G. Vayas,"Sensors for Parkinson's disease evaluation," 2017 International Caribbean Conference on Devices, Circuits and Systems (ICCDCS), 2017, pp. 121-124

[8]. C. Quan, K. Ren and Z. Luo,"a Deep Learning Based Method for Parkinson's Disease Detection Using Dynamic Features of Speech."IEEE Access, vol. 9,pp. 10239-10252,2021.

[9]. O.Asmae, R.Abdelhadi, C.Bounchaib, S.Sara and K. Taheddine, "Parkinsons Disease Identification Using KNN and ANN Algorithms based on Voice Disorder,"2020 1st International Canference On Innovative Research In Applied Science, Engineering and Technology (IRASET),2020.

[10]. Sakar, C. Okan; Serbes Gorkem; Gunduz, Aysegul; Tunc, Hunkar C.; Nizam Hatice; Sakar Betul Erdogdu;Tutuncu Melih Aydin,Tarkan; Isenkul, M.Erdem; Apaydin, Hulya(2018). A comparative analysis of speech signal processing algorithms for Parkinson's disease classification and the use of the tunable Q-factor wavelet transform. Applied Soft Computing, (), S1568494618305799.

[11]. M.S.Islam, I.Parvez, Hai Deng, And P. Gpswami,"performance Comparison Of Heterogeneous Classifirs For Detection Of Parkinsons Disease Using voice disorder (dysphonia)," 2014 International Conference on Informatics, Electronics & Vision (ICIEV), 2014, pp.

[12]. L. Ali, C. Zhu, N. A. Golilarz, A. Javeed, M. Zhou and Y. Liu, "Reliable Parkinson's Disease Detection by Analyzing Handwritten Drawings: Construction of an Unbiased Cascaded Learning System Based on Feature Selection and Adaptive Boosting Model," in IEEE Access, vol. 7, pp. 116480-116489, 2019,

[13]. Esmaeilzadeh, Soheil, Yao Yang, and Ehsan Adeli. "End-to-end parkinson disease diagnosis using brain mr-images by 3d-cnn." arXiv preprint arXiv:1806.05233 (2018).

[14]. Saravanan, S., Ramkumar, K., Adalarasu, K. et al. A Systematic Review of Artificial Intelligence (AI) Based Approaches for the Diagnosis of Parkinson's Disease. Arch Computat Methods Eng (2022).

[15]. DeMaagd G, PharmD BCPS, Ashok Philip P (2015) Parkinson's disease and its management.

[16]. Ball, Nicole; Teo, Wei-Peng; Chandra, Shaneel; Chapman, James (2019). Parkinson's Disease and the Environment. Frontiers in Neurology, 10(), 218–. doi:10.3389/fneur.2019.00218

[17]. Goyal, J., Khandnor, P., &Aseri, T. C. (2020). Classification, Prediction, and Monitoring of Parkinson's disease using Computer Assisted Technologies: A Comparative Analysis. Engineering Applications of Artificial Intelligence, 96, 103955. doi:10.1016/j.engappai.2020.

[18]. Richens JG, Lee CM, Johri S (2020) Improving the accuracy of medical diagnosis with causal machine learning. Nat Commun11:1–9

[19]. Ray Dorsey E, Elbaz A (2018) Global, regional, and national burden of Parkinson's disease, 1990–2016: a systematic analysis for the global burden of disease study 2016.

[20]. Jakel, Rebekah J., and Mark Stacy. "Parkinson's disease psychosis." Research and Reviews in Parkinsonism 4 (2014): 41-51.

[21]. A. H. Butt, F. Cavallo, C. Maremmani and E. Rovini, "Biomechanical parameters assessment for the classification of Parkinson Disease using Bidirectional Long Short-Term Memory*," 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 2020,

[22]. Cavallo, Filippo; Moschetti, Alessandra; Esposito, Dario; Maremmani, Carlo; Rovini, Erika (2019). Upper limb motor pre-clinical assessment in Parkinson's disease using machine learning.

[23]. Saha, Roshni. "Classification of Parkinson's disease using MRI data and deep learning convolution neural networks." Creative Components 241 (2019).

[24]. S. Raval, R. Balar and V. Patel, "A Comparative Study of Early Detection of Parkinson's Disease using Machine Learning Techniques," 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184), 2020, pp. 509-516, doi: 10.1109/ICOEI48184.2020.9142956.

[25]. Drissi, Taoufiq Belhoussine, et al. "Diagnosis of Parkinson's disease based on wavelet transform and mel frequency cepstral coefficients." Int. J. Adv. Comput. Sci. Appl 10 (2019). 125-132.

[26]. Lahmiri, S., Shmuel, A., 2019. Detection of Parkinson's disease based on voice patterns ranking and optimized support vector machine. Biomed. Signal Process. Control 49, 427–433.

[27]. Sharma, P., Sundaram, S., Sharma, M., Sharma, A., Gupta, D., 2019. Diagnosis of Parkinson's disease using modified grey wolf optimization. Cogn. Syst. Res. 54, 100–115.

[28]. Kadam, V.J., Jadhav, S.M., 2019. Feature ensemble learning based on sparse autoencoders for diagnosis of Parkinson's disease. In: Computing, Communication and Signal Processing. Springer, pp. 567–581.

[29]. Shukla, A.K., Singh, P., Vardhan, M., 2019. Medical diagnosis of Parkinson disease driven by multiple preprocessing technique with Scarce Lee Silverman voice treatment data. In: Engineering Vibration, Communication and Information Processing. Springer, pp. 407–421.

[30]. Almeida, J.S., Rebouças Filho, P.P., Carneiro, T., Wei, W., Damaševičius, R., Maskeliunas, R., de Albuquerque, V.H.C., 2019. Detecting Parkinson's disease with sustained phonation and speech signals using machine learning techniques. Pattern Recognit. Lett. 125, 55–62.

[31]. Moro-Velázquez, L., Gómez-García, J.A., Godino-Llorente, J.I., Villalba, J., Orozco-Arroyave, J.R., Dehak, N., 2018. Analysis of speaker recognition methodologies and the influence of kinetic changes to automatically detect Parkinson's disease. Appl. Soft Comput. 62, 649–666.

[32]. Tuncer, T., Dogan, S., 2019. A novel octopus based Parkinson's disease and gender recognition method using vowels. Appl. Acoust. 155, 75–83.

[33]. Zhang, Y., 2017. Can a smartphone diagnose parkinson disease? a deep neural network method and telediagnosis system implementation. Park. Dis. 2017.

[34]. Frid A, Kantor A, Svechin D, Manevitz LM (2016) Diagnosis of Parkinson's disease from continuous speech using deep convolution networks without manual selection of features. In: 2016 IEEE International Conference on the Science of Electrical Engineering (ICSEE).

[35]. Oh SL, Hagiwara Y, Raghavendra U, Yuvaraj R, Arunkumar N, Murugappan M, Acharya UR (2018) A deep learning approach for Parkinson's disease diagnosis from EEG signals. Neural Comput Appl.

[36]. Zhao A, Qi L, Li J, Dong J, Yu H (2018) A hybrid spatio-temporal model for detection and severity rating of Parkinson's disease from gait data.

[37]. Caliskan A, Badem H, Basturk A, Yuksel ME (2017) Diagnosis of the Parkinson disease by using deep neural network classifier. IU-J Electr Electron Eng 17(2):3311–3318

[38]. Gunduz H (2019) Deep learning-based Parkinson's disease classification using vocal feature sets. IEEE Access 7:115540–115551.

[39]. Al-Fatlawi AH, Jabardi MH, Ling SH (2016) An efficient diagnosis system for Parkinson's disease using deep belief network In: 2016 IEEE Congress on Evolutionary Computation (CEC), pp 1324–1330. IEEE

[40]. Wodzinski M, Skalski A, Hemmerling D, Orozco-Arroyave JR, Noth E (2019) Deep learning approach to Parkinson's disease detection using voice recordings and convolution neural network dedicated to image classification. Proc Annu Int Conf IEEEEng Med Biol Soc EMBS.

[41]. Dai Y, Tang Z, Wang Y, Xu Z (2019) Data driven intelligent diagnostics for Parkinson's disease. IEEE Access 7:106941–106950.

[42]. Alharthi AS and Ozanyan KB (2019) Deep learning for ground reaction force data analysis: Application to wide-area floor sensing. In: 2019 IEEE 28th Int Symp Ind Electron (ISIE), pp 1401–1406. IEEE

[43]. Pahuja G, Nagabhushan TN, Prasad B (2020) Early detection of Parkinson's disease by using SPECT imaging and biomarkers. J Intell Syst 29:1329–1344.

[44]. Gil-Martín M, Montero JM, San-Segundo R (2019) Parkinson's disease detection from drawing movements using convolution neural networks. Electron 8:1–10.

[45]. Banerjee M, Chakraborty R, Archer D, Vaillancourt D and Vemuri BC (2019) Dmr-cnn: A cnn tailored for dmr scans with applications to pd classifcation." In: 2019 IEEE 16th Int Symp Biomed Imaging (ISBI 2019), pp 388–391. IEEE

[46]. Sharma P, Sundaram S, Sharma M, Sharma (2019) Multiclass diagnosis of neurodegenerative diseases: a neuroimaging machine-learning-based approach †. NeuroImage Clin 7:21710–21745.

[47]. Peng B, Wang S, Zhou Z, Liu Y, Tong B, Zhang T, Dai Y (2017) A multilevel-ROI-features-based machine learning method for detection of morphometric biomarkers in Parkinson's disease. Neurosci Lett 651:88–94.

[48]. Georgiopoulos C, Witt ST, Haller S, Dizdar N, Zachrisson H, Engström M, Larsson, (2019) A study of neural activity and functional connectivity within the olfactory brain network in Parkinson's disease. NeuroImage Clin 23:1491–1496.

[49]. Sateesh Babu G, Suresh S, Mahanand BS (2014) A novel PBL-McRBFN-RFE approach for identification of critical brain regions responsible for Parkinson's disease. Expert Syst Appl 41:478–488.

[50]. Abós A, Baggio HC, Segura B, García-Díaz AI, Compta Y, Martí MJ, Valldeoriola F, Junqué C (2017) Discriminating cognitive status in Parkinson's disease through functional connectomics and machine learning. Sci Rep 7:1–13.

[51]. Rubbert C, Mathys C, Jockwitz C, Hartmann CJ, Eickhof SB, Hofstaedter F, Caspers S, Eickhof CR, Sigl B, Teichert NA, Südmeyer M (2019) Machine-learning identifes Parkinson's disease patients based on resting-state between-network functional connectivity. Br J Radiol 92(1101):20180886

[52]. Rana B, Juneja A, Saxena M, Gudwani S, Senthil Kumaran S, Agrawal RK, Behari M (2015) Regions-of-interest based automated diagnosis of Parkinson's disease using T1-weighted MRI.Expert Syst Appl 42:4506–4516.

[53]. Zhang L, Liu C, Zhang X, Tang YY (2017) Classification of Parkinson's disease and essential tremor based on structural MRI. Proc - 2016 7th Int Conf Cloud Comput Big Data, CCBD.

[54]. Chen Y, Yang W, Long J, Zhang Y, Feng J, Li Y, Huang B (2015) Discriminative analysis of Parkinson's disease based on whole brain functional connectivity. PLoS ONE 10:1–16.

[55]. Adeli E, Shia F, Ana L, Weea CY, b, Wua G, Wanga T, c, d and DS (2016) Joint feature-sample selection and robust diagnosis of Parkinson's disease from MRI data. Neuroimage 176:1570–1573.

[56]. Kazeminejad A, Golbabaei S, Soltanian-Zadeh H (2018) Graph theoretical metrics and machine learning for diagnosis of Parkinson's disease using rs-fMRI. 19th CSI Int Symp Artif Intell Signal Process AISP 2017, pp 134–139

[57]. Zeng LL, Xie L, Shen H, Luo Z, Fang P, Hou Y, Tang B, Wu T, Hu D (2017) Differentiating patients with Parkinson's disease from normal controls using gray matter in the cerebellum. Cerebellum 16:151–15