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A Survey on Diagnosing Parkinson's Disease Severity in Patients

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Abstract: Parkinson's Disease (PD) is a progressive neurodegenerative disorder with diverse symptom trajectories, complicating the accurate assessment of disease severity. Precise evaluation is critical for treatmentplanning and personalized care. This survey presents a comprehensive review of computational approaches developed between 2021 and 2025 for PD severity diagnosis, focusing on machine learning and deep learning techniques across multiple data modalities, including gait, voice, neuroimaging, and multimodal sensors. Methods range from traditional classifiers like SVM and Random Forests to advanced models such as CNNs, BiLSTMs, and Transformers. Gait-based models using wearable data have achieved over 97% accuracy, while voice-based systems using LightGBM and XGBoost report up to 96% accuracy. Imaging models leveraging CNN variants on MRI and EEG data exceed 98% performance, particularly when combined with demographic normalization. Multimodal frameworks integrating clinical, demographic, and physiological data show strong diagnostic capability, with AUC values reaching 1.0 in severity classification. Despite promising results, challenges remain in data diversity, sample size limitations, model interpretability, and clinical scalability. This paper identifies current trends such as mobile-basedmonitoring, longitudinal modeling, and explainable AI, offering insights for the development of robust and generalizable PD severity assessment tools.
Keywords: Parkinson's Disease, Severity Assessment, Machine Learning, Deep Learning, Biomedical Signals, Multimodal Analysis

1. INTRODUCTION

Parkinson's Disease (PD) is a chronic, progressive neurodegenerative disorder, which has an impact on the movements, balance, and coordination as well asa number of non-motor processes. It usually causes tremor, rigidity, bradykinesia, posturalim balance and mental or speech disturbances. PD affects more than 10 million people around the world and it is an ever increasing concern, particularly in elderly peoplewho already suffer problems with healthcare needs [4].In order to effectively deal with PD, it is essential to gain an understanding of the severity of the condition in a given patient. It assists the doctors to make decisions on treatments and monitor the effectiveness of the treatments. Now, the majority of neurologists use rating scales such as Unified Parkinson Disease Rating Scale (UPDRS) or Hoehn and Yahr scale. Though these tools are not new in clinicalpracticeastheyhave beenusedoverdecades, there are problems associated with it. In the first place, the scores may differ among doctors and various patients may express various mixes of symptoms [2]. These issues have prompted researchers to seek ways of making the severity assessment more objective. With the fast development of machine learning (ML) and deep learning (DL), people also show interest in developing code or tools that could assess the level of PD via information. As one illustration, wearable sensors have been utilized in the study of walking patterns [3], voice signals that contain information about speech changes have been recorded [14], and brainscanssuchasMRI and EEGhavebeenanalyzed [15]. Other studies even use a combination of various types of data in order to be more accurate in forecasts combining, e.g., clinical notes, sensor data, andpatient history data [1], [17]. What few other reviews have examined is available, however, on the topic of AI in general PD diagnosis [5], [23], but not on the issue of determining the severity of the disease. Since 2021, the scientists have created even more advanced mechanisms like hybrid DL models and transformer networks, which are enabled to process several types of data simultaneously.

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This paper summarizes these new studies (20212025) in a comparative study of the various approaches to AI, their extent of success, and the limitations to success that are still true today. It also brings out emerging trends, such as the real-time symptom monitoring and understandable artificial intelligence system that can assist doctors in getting a better insight into what the models are performing. This should provide researchers and clinicians with a clear and most recent overview of the way in whichAI is assisting us in our push towards a more reliable and personalized method of assessing PD severity.

II. LITERATURE SURVEY

The evolution of Parkinson's Disease (PD) diagnosis has transitioned from traditional symptom-based methods to objective, data-driven frameworks. This shift is largely due to the clinical complexity of PD, with its variable symptom presentation and overlap with other neurodegenerative conditions. Among early biomarkers, speech abnormalities particularly hypokinetic dysarthria have emerged as a practical and non-invasive target. Rana et al. [13] demonstrated that voice features analyzed with artificial neural networks (ANN) could accurately classify PD severity, achieving 96.7% accuracy. Similarly, Suppa et al. [14] used support vector machines (SVM) to distinguish PD stages and medication states through acoustic markers, introducing a new metric that correlated stronglywith clinical assessments.

Building on these efforts, Chen et al. [15] developeda deep convolutional neural network (DCNN) optimized with a chimp algorithm, achieving over 96% accuracy in detecting speech-related impairments.Inparallel, motion-basedanalysisusing inertial measurement units (IMU) has gained prominence. Lin et al. [16] designed a neural model that detected early-stage PD with 99.67% accuracy, highlighting the sensitivity of biomechanical signals. A broader analysis by Skaramagkas et al. [17] affirmed that deep learning models like CNNs and LSTMs consistently outperformed classical techniques across various data types—speech, gait, and facial expressions—though interpretability remains a hurdle. Erdaş et al. [18] addressed this by integrating ConvLSTM and 3D CNNs for gait analysis, capturing both spatial and temporal patterns effectively. Beyond motor symptoms, Hemmerling and Wojcik-Pedziwiatr [19] linked vowel-based acoustic features to UPDRS scores using regression, enabling non-invasive tracking of medication efficacy. Cosentino et al. [20] highlighted dysphagia as an under recognized symptom and supported AI- assisted screening for improved severity detection.

Onthe molecular front, Rutledgeetal.[21]identified DOPA decarboxylase (DDC) as a key biomarker correlated with PD progression via large-scale proteomic profiling. Vidya and Sasikumar [22] used vertical ground reaction force (VGRF) and a CNN– LSTM hybrid to achieve 98.32% classification accuracy, reinforcing the role of wearable sensors. Saravanan et al. [23] emphasized multimodal fusion as a way to improve diagnostic accuracy by combining diverse signals like EEG, gait, and imaging data. Immune profiling has also gained relevance. Bhatia et al. [24] found decreased CD8+T-cells and heightened inflammatory markers in severe PD cases. Similarly, Meloni et al. [25] used extracellular vesicles to differentiate PD from a typical parkinsonian syndromes, with α-synuclein levels correlating with disease severity. Pedersen et al. [26] assessed pS129-α-syn levels across fluids, suggesting its utility as part of a biomarker panel. Lastly, Lamba et al. [27] used genetic algorithms and random forests on imbalanced speech datasets, achieving 95.58% accuracy—further showcasing the maturity of AI tools in PD severity estimation. Figure 1illustrates the annual distribution of key research contributions from 2021 to 2025, reflecting the growing emphasis on computational methods for Parkinson's Disease severity diagnosis.

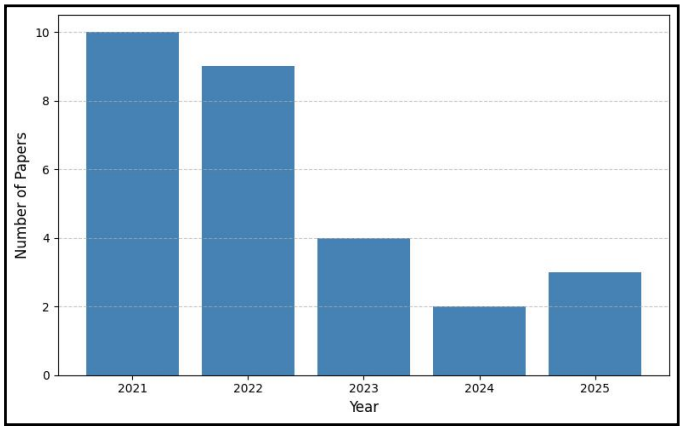

Fig1: Distribution of Parkinson's Disease Research Publications (2021–2025)

3. MODALITIES FOR PD SEVERITY DIAGNOSIS

The identification and grading of Parkinson's Disease (PD) severity have become increasingly modality- driven, with researchers leveraging a range of physiological, behavioral, and molecular data sources. Each modality offers unique insights into thedisease's progression and symptom variability, shaping the development of tailored diagnosticmodels.

3.1 Gait and Movement Analysis

Gait abnormalities are hallmark motor symptoms of PD and are often among the earliest indicators of disease onset. Techniques using time-series data from inertial measurement units (IMUs) have demonstrated high sensitivity to subtle movement impairments. Models combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have shown exceptional performance in distinguishing PD severity levels based on gait patterns [3], [8], [22], [30].

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For instance, Vidya and Sasikumar [22] used vertical ground reaction force (VGRF) signals in a hybrid CNN-LSTM architecture, achieving an accuracy of over 98% in multiclass severity classification. Erdaş et al. [18] expanded on this by integrating 3D CNNs and ConvLSTM to capture complex spatial-temporal dynamics in gait, particularly useful for modeling progressive motor deterioration. Moreover, Cosentino et al. [20] brought attention to dysphagia—another movement-related symptom advocating its inclusion in motor severity assessment due to its underdiagnosed yet significant impact.

3.2 Voice and Speech Biomarkers

Voice has emerged as a non-invasive, cost-effective modality for monitoring PD. Studies have identified hypokinetic dysarthria, characterized by reduced pitch variability and speech clarity, as a measurable indicator of severity. Rana et al.[13] and Suppa et al. [14] applied machine learning(ML) and support vector machines (SVM) to acoustic features, successfully predicting PD stages and treatment states. Hemmerling and Wojcik-Pedziwiatr [19] demonstrated the feasibility of using vowel-based voice data to estimate Unified Parkinson's Disease Rating Scale (UPDRS) scores via regression models. Lamba et al. [27] optimized feature selection and classification using genetic algorithms and Random Forests, addressing class imbalance with SMOTE to boost model generalizability. In a similar context, Sharma et al. [7] implemented an ensemble KNN classifier on imbalanced datasets, achieving high accuracy in speech-based diagnosis. Severity estimation was also successfully attempted through voice in conjunction with clinical markers [11].

3.3 Neuro imaging and Bio-Signals

Neuroimaging techniques, particularly magnetic resonance imaging (MRI), offer structural and functional perspectives on PD pathology. Chenetal. [15] utilized CNNs on MRI data to identify PD- related brain abnormalities. Beyond imaging, bio fluid biomarkers have become central in recent diagnostic strategies. Bhatia et al. [24] and Meloni et al. [25] examined cerebrospinal fluid (CSF) and extracellular vesicles, linking elevated levels of α-synuclein and inflammatory markers with increasing PD severity. Pedersen et al. [26] added to this with a review of phosphorylated alpha-synuclein (pS129-α-syn) in blood and CSF, supporting its role in longitudinal tracking. In the biochemical domain, Rutledgeetal. [21] and Tripathietal.[10] identified severity-related signatures in plasma and gutmicrobiota, emphasizing systemic biomarkers. These findings underscore how molecular changes precede or complement clinical manifestations [28].

3.4 Multimodal Fusion Approaches

Combining multiple data streams often enhances the reliability of severity assessments. Skaramagkas et al. [17] emphasized the superiority of multimodal deep learning frameworks in capturing the multidimensional nature of PD. Models integrating voice, gait, clinical scores, and demographics have demonstrated improved robustness [1],[9].A notable example includes lipidomic data fused with ML techniques to stratify PD severity [12]. Hybrid systems like the one proposed by Lamba et al. [27] exemplify how fusion of optimized voice featuresand machine learning algorithms can achieve high diagnostic accuracy even in real-world, imbalanced datasets. Overall, modality-specific approaches each offer critical advantages: voice for early detection, gait for motor severity, imaging and bio-signals for pathophysiological insight, and multimodal fusion for comprehensive, personalized assessment.

4. ML/DL METHODOLOGIES FOR PD SEVERITY ASSESSMENT

The selection of machine learning (ML) or deep learning (DL) models plays a central role in the accuracy and reliability of Parkinson's Disease (PD) severity assessment. Over the past decade, researchers have explored a spectrum of methodologies from classic ML classifiers to hybrid and advanced deep learning architectures each with varying success in predicting clinical outcomes suchas UPDRS scores, medication response, andmulticlass severity levels.

4.1 Traditional ML Models

Classic ML techniques such as k-nearest neighbors (KNN), support vector machines (SVM), Random Forest (RF), and ensemble methods remain popularfor their interpretability and low computational overhead. Rana et al. [13] applied multiple supervised models to voice data, finding that artificial neural networks (ANN) and RF outperformed KNN and Naïve Bayes, with ANN achievinga peakaccuracyof 96.7%. Similarly, Lamba et al. [27] used RF with genetic algorithm-based feature selection to reach 95.58% accuracy on imbalanced speech datasets, enhanced further using SMOTE. Sharma et al. [7] leveraged ensemble KNN with feature engineering techniques to achieve competitive classification accuracy. Other studies, such as Tripathi et al. [12], applied LightGBM and XGBoost to lipidomic datasets, highlighting the adaptability of traditional ML for non-motor biomarker prediction. A comprehensive analysis by Thangavel et al. [1] summarized that traditional models still perform well when data quality and feature selection are optimal. Furthermore, studies like Ahmad et al. [11] compared classical ML with DL methods and found that while ML models are efficient with small datasets, DL models excel in complex feature abstraction and multimodal learning scenarios.

4.2 Deep Learning Models

DL models, particularly CNNs and LSTMs, have shown exceptional results in modeling spatial and temporal patterns in gait, EEG, and speech data. For example, Vidya and Sasikumar [22] implemented a CNN–LSTM hybrid on vertical ground reaction force signals, achieving 98.32% accuracy in multiclass PD severity classification. Linetal.[8] and Chenetal. [15] applied CNNs to motion sensor and MRI data respectively, extracting high-level features for effective classification.Inneuroimaging,deep models have also been used for EEG and MRI-baseddiagnosis with promising results [9], [16]. Skaramagkas et al. [18] demonstrated how combining ConvLSTM and 3D CNN architectures could model gait transitions and motor decline with high temporal resolution. ANN models have also been used for gait- based classification, with some studies reporting accuracies exceeding 99% for early-stage PD [30].

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4.3 Hybrid and Advanced Architectures

To overcome limitations of single-model approaches, hybrid systems have emerged as a powerful solution. Chen et al. [15] introduced a CNN architecture optimized through the chimp optimization algorithm, which improved speech classification accuracy by fine-tuning hyper parameters adaptively. Skaramagkas et al. [17] reviewed the application of transformer- based and attention mechanisms in PD classification, particularly in multimodal fusion contexts. HybridDL architectures combining CNNs with attention blocks or recurrent units have also been explored for EEG and motor data [1], [9]. Lamba et al. [27] demonstratedhowmergingevolutionaryoptimization with ML classifiers produced robust performance across unbalanced voice datasets. Saravanan et al.[23] further categorized PD detection models by AI paradigm ranging from rule-based systems to explainable DL emphasizing that advanced architectures not only boost accuracy and AUC but also support clinical interpretability. Overall, while traditional ML remains relevant for well-structured datasets, DL and hybrid models outperform in tasks involving complex signals or multimodal inputs. Performance metrics across studies commonly report accuracy above 90%, with some exceeding 98% in UPDRS prediction, particularly when combining optimized model architectures with domain-specific feature engineering.

5. PERFORMANCE EVALUATION

Table1: Performance Evaluation of ML/DL Models in PD Severity Assessment

Modality	Model	Task	Accuracy / AUC	Dataset
Gait	LSTM[3]	UPDRS regression	94%	Custom
Gait	CNN[8]	Classification	97.5%	Custom
Voice	LightGBM [13]	Severity classification	96%	UCI PD
Voice	SVM[14]	ON/OFF medication state	95.2%	Clinical
MRI	CNN+ ChOA Optimizer [15]	Disease detection	98%	Public
Motion sensor	DNN[16]	EarlyPD detection	99.67%	Inertial data
Multimodal	Transformer based DL [17]	Severity stage classification	AUC= 1.0	Mixed
Gait	Conv LSTM + 3D CNN[18]	Classification	96.1%	Custom
Voice	Linear Regression [19]	UPDRS estimation	R^2= 0.89	Acoustic signals
Gait	CNN– LSTM [22]	Multiclass classification	98.32%	VGRF data
Voice	GA+RF [27]	Severity classification	95.58%	UCI PD + SMOTE
Gait	ANN[30]	Severity detection	94.6%	Motion sensor
Voice	Ensemble KNN [7]	Imbalanced classification	91.2%	Customspeech
MRI+ EEG	CNN + BiLSTM[9]	Hybrid diagnosis	97.8%	Clinical
Lipidomics	XGBoost +Feature Selection [12]	Diagnosis	94.3%	Metabolic data
Clinical	Naïve Bayes, SVM[2]	Risk prediction	85%	Clinical
Epidemiology	Logistic Regression [4]	Symptom progression	87%	Population data
Wearable data	SVM+ Sensor Fusion[5]	Real-time monitoring	93.5%	IMU sensor
EEG	CNN[6]	Severity classification	96.2%	EEG recordings

Table 1 summarizes the performance of machine learning and deep learning models across various modalities for Parkinson's Disease severity assessment. It highlights model types, targeted tasks (e.g., classification, UPDRS regression), and corresponding performance metrics such as accuracy or AUC. Modalities include gait, voice, MRI, EEG, and multimodal fusion, demonstrating the diversity of diagnostic approaches. Most deep learning models, particularly CNN and LSTM variants, consistently achieved high accuracy (>94%). Dataset types range from public repositories like UCI PD to clinical and custom-collected sensor data.

6. CHALLENGES AND LIMITATIONS

Despite the significant advances of technology in terms of aiding the diagnosis of Parkinson Disease (PD), the implementation of AI in a real clinical setting in a positive way is not seamless as one might think. The nature of the standardized scales such as UPDRS where doctors varies in their interpretation is one of the chronic issues. Although these tools are expected to introduce consistency, there have been variationsinthedeterminationofthesetoolsbetween the assessor or even in clinics [2], [4]. In addition to clinical paths, there are technical barriers as well. Standardization of machine learning (ML) design and evaluation strategies does not appear to be the norm. Individual studiesare likelyto make their own use of datasets, preprocessing, and performance criteria, and thus it is hard to compare results across studies [5], [23]. In addition to that, much of the data is either very small or not diverse enough in terms of the demographics of patients.This hinders the model from dealing with other instances in the wider population [1], [7], [17]. Oneof the problems that frequently arises and appears to be particularly prevalent in speech and movement data is imbalance; i.e., having disproportionatelylarge numbers of mild cases in the dataset relegating models to perform poorly on more severe phases. Another thorn is interpretability. It is also understandable that clinicians will be cautious in using instruments that they cannot explicate more especially when they are being used as guides in making treatment decisions. According to a study by Suppa et al. [14], transparency of an AI model is highly important, as an AI model that is unable to demonstrate its decision-making process is unlikelyto be trusted by a clinician.

Finally, information coming in from various sources, such as gait sensors, medical imaging, or voice records, can possess diversity in terms of format and quality. This complicates integration and may decrease the reliability of the model's operation. These worries highlight the importance of the necessity of explainable systems, common standards, and the deployment thereof, in the healthcare area that is thought through and stays ethical.

7. EMERGING TRENDS & FUTURE WORK

Research in Parkinson's diagnosis is beginning to move away from single-source analysis toward smarter, more comprehensive systems. Many teams are now building models that combine voice data,gait patterns, facial expressions, and sensor outputs to allow for real-time monitoring even when the patient isn't at the clinic [17]. These systems aim to offer more continuous and personalized tracking of disease progression. At the same time, there's been a surge of interest in identifying biological markers in body fluids that might point to PD severity. Biomarkers like alpha-synuclein and DOPA decarboxylase, found in cerebrospinal fluid or blood plasma, are showing promise for early diagnosiswhen paired with AI systems [21], [25], [26]. Some studies are also exploring new and unexpected data sources. For instance, research into the gut-brain link has opened the door to using lipid profiles and metabolites like short-chain fatty acids (SCFAs) as diagnostic clues [10], [12], [28]. And from a technical perspective, there's growing attention on federated learning—a method that allows hospitals to train shared AI models without moving sensitive patient data across institutions [23]. Throughout all of this, one thing remains clear: transparency is key. Explainable AI (XAI) is more than just a buzzword— it's what will allow doctors to trust and adopt these tools in daily practice.

8. CONCLUSION

In conclusion, there have been significant advancements made concerning the utilization of machine learning (ML) and deep learning (DL) in the estimation of the severity of Parkinson's Disease. Radiology Experts in voice and gait analysis, biological signal mining, etc. Using these methods, earlier detectable and more precise measurements can be done to monitor conditions. Advanced neural structures, preservation of multimodal data, and targeting optimization methods have significantly enhanced the speed and accuracy of the predictions and their sensitivity to changes in symptoms. Nonetheless, clinical translation is still used only in moderation.Themajorityofmodelsremainlimitedby small data sets, non-standardized nature, and the difficulty in applying the model to other populations. To pursue these developments in the future, the consideration of large-scale validation, real-world applicability, and the formulation of explainable, patient-focused AI systems are the top priorities. It is only such efforts that will see the development ofthese technologies to become part of the clinical decision-making process of Parkinson's disease care.

REFERENCES

1. Ayaz, Z., Naz, S., Khan, N. H.,Razzak, I., & Imran, M. (2023). Automated methods for diagnosisof Parkinson's disease and predicting severity level. NeuralComputingandApplications,35(20),14499-14534.
2. Tolosa,E.,Garrido,A.,Scholz,S.W.,&Poewe,W.(2021).Challenges in the diagnosis of Parkinson's disease. The Lancet Neurology, 20 (5),385-397.
3. Balaji,E.,Brindha,D.,&Umesh,K.(2021).Data- driven gait analysis for diagnosis and severity ratingof Parkinson's disease. Medical Engineering &Physics,91,54-64.
4. Bloem, B. R., Okun, M. S., & Klein, C. (2021). Parkinson'sdisease.TheLancet,397(10291),2284-2303.
5. Mei, J.,Desrosiers, C.,&Frasnelli, J. (2021). Machine learning for the diagnosis of Parkinson's disease: a review of literature. Frontiers in aging neuroscience,13,633752.
6. Sibley,K.G.,Girges,C., Hoque,E.,&Foltynie,T. (2021). Video-based analyses of Parkinson's disease severity: a brief review. Journal of Parkinson'sdisease,11(s1),S83-S93.
7. Zhao,H.,Wang, R., Lei, Y.,Liao,W.H., Cao,H., & Cao, J. (2022). Severity level diagnosis of Parkinson's disease by ensemble K-nearest neighbor under imbalanced data. Expert Systems with Applications, 189,116113.
8. Balaji, E., Brindha, D., &Vikrama, R. (2021). Automatic and non-invasive Parkinson's disease diagnosis and severity rating using LSTM network. AppliedSoftComputing,108,107463.
9. Aşuroğlu, T., &Oğul, H. (2022). A deep learning approach for parkinson's disease severity assessment. Health and Technology, 12(5),943-953.
10. Chen,S.J.,Chen,C.C.,Liao,H.Y.,Lin,Y.T.,Wu,Y.W.,Liou,J.M &Lin,C.H.(2022). Association of fecal and plasma levels of short-chain fatty acids with gut microbiota and clinical severity in patients with Parkinson disease.Neurology, 98(8), e848-e858.
11. Raundale, P.,Thosar, C.,& Rane, S. (2021, May). Prediction of Parkinson's disease and severity of the disease using Machine Learning and Deep Learning algorithm. In 2021 2nd International Conference for Emerging Technology (INCET) (pp. 1-5). IEEE.
12. Avisar, H., Guardia-Laguarta, C., Area-Gomez, E., Surface, M., Chan, A. K., Alcalay, R. N., & Lerner, B. (2021). Lipidomics prediction of Parkinson's disease severity: a machine-learning analysis. Journal of Parkinson's Disease, 11(3),1141-1155.
13. Rana, A., Dumka, A., Singh, R., Rashid, M., Ahmad, N., & Panda, M. K. (2022). An efficient machine learning approach for diagnosing Parkinson's disease by utilizing voice features. Electronics, 11(22), 3782.
14. Suppa,A.,Costantini,G.,Asci,F.,DiLeo,P.,Al-Wardat, M. S., Di Lazzaro, G., ...&Saggio, G. (2022). Voice in Parkinson's disease: a machine learning study. Frontiers in neurology,13,831428.
15. Chen,F.,Yang,C.,&Khishe, M.(2022). Diagnose Parkinson's disease and cleft lip and palate using deep convolutional neuralnetworksevolved by IP-based chimp optimization algorithm. Biomedical Signal Processing and Control,77,103688.

ISSN: 2393-9842
https://www.irjcs.com/archives
https://doi.org/10.26562/irjcs.2025.v1209.01

16. Lin,C.H.,Wang,F.C.,Kuo,T.Y.,Huang,P.W., Chen, S. F., & Fu, L. C. (2022).Early detection of Parkinson's disease by neural network models.IEEE Access, 10,19033-19044.
17. Skaramagkas, V., Pentari, A., Kefalopoulou, Z., &Tsiknakis, M. (2023). Multi-modal deep learning diagnosis of Parkinson's disease a systematic review. IEEE Transactions on Neural Systems and RehabilitationEngineering,31,2399-2423.
18. Erdaş, Ç.B.,Sümer, E.,&Kibaroğlu, S.(2021). Neurodegenerative disease detection and severity prediction using deep learning approaches. Biomedical Signal Processing and Control, 70, 103069.
19. Hemmerling, D., &Wojcik-Pedziwiatr, M. (2022). Prediction and estimation of Parkinson's disease severity based on voice signal. Journal of Voice,36(3),439-e9.
20. Cosentino, G., Avenali, M., Schindler, A., Pizzorni, N., Montomoli, C., Abbruzzese, G., ...&Alfonsi, E. (2022). A multinational consensus on dysphagia inParkinson's disease: screening, diagnosis and prognostic value. Journal of Neurology, 269(3), 1335-1352.
21. Rutledge,J.,Lehallier,B.,Zarifkar,P.,Losada,P.M.,Shahid-Besanti,M.,Western,D.,...&Poston,K.L.(2024).Comprehensive roteomics of CSF, plasma, and urine identify DDC and other biomarkers of early Parkinson's disease. Actaneuro pathologica, 147(1), 52.
22. Vidya,B.,& Sasikumar,P.(2022).Parkinson's disease diagnosis and stage prediction based on gait signal analysis using EMD and CNN–LSTM network. Engineering Applications of Artificial Intelligence, 114,105099.
23. Saravanan, S., Ramkumar, K., Adalarasu, K., Sivanandam, V., Kumar, S. R., Stalin, S., &Amirtharajan, R. (2022). A systematic review of artificial intelligence (AI) based approaches for the diagnosis of Parkinson's disease. Archives of computationalmethodsinengineering,29(6),3639-3653.
24. Bhatia,D.,Grozdanov,V.,Ruf,W.P.,Kassubek,J., Ludolph,A.C.,Weishaupt, J.H.,&Danzer, K. M. (2021).T-celldys regulation is associated with disease severity in Parkinson's Disease. Journal of neuro inflammation, 18(1), 250.
25. Meloni, M., Agliardi, C., Guerini, F. R., Zanzottera,M.,Bolognesi,E.,Picciolini,S.,& Clerici, M. (2023).Oligomeric α-synuclein and tau aggregates in NDEVs differentiate Parkinson's disease from atypical parkinsonisms. Neurobiology of Disease,176,105947.
26. Pedersen, C.C.,Maple-Grødem, J., & Lange, J. (2025). A systematic review of bio fluid phosphorylated α-synuclein in Parkinson's disease. Parkinsonism&RelatedDisorders,132,107240.
27. Lamba, R.,Gulati, T.,Alharbi, H.F., & Jain, A.(2022). A hybrid system for Parkinson's disease diagnosis using machine learning techniques. International Journal of Speech Technology, 25(3), 583-593.
28. Zhang,Y.,He,X.,Qian,Y.,Xu,S.,Mo,C.,Yan, Z.,&Xiao,Q.(2022).Plasma branched-chain and aromatic amino acids correlate with the gutmicrobiota and severity of Parkinson's disease. npj Parkinson's Disease, 8(1), 48.
29. Onder, H., Gunaydin, A., Erdogan, N., &Comoglu,S.(2025).Investigation of the Determinants of Disease Severity in Patients with Idiopathic Normal Pressure Hydrocephalus. Movement Disorders Clinical Practice.
30. Varrecchia, T., Castiglia, S. F., Ranavolo, A., Conte, C., Tatarelli, A., Coppola, G., ...&Serrao, M. (2021). An artificial neural network approach to detect presence and severity of Parkinson's disease via gait parameters. PLoS One, 16(2), e0244396.

