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Optimized Vmd-1d CNN Framework for Real-Time and Early Detection of Parkinson's Disease from Gait Dynamics

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Abstract-Parkinson's disease (PD) significantly impairs gait dynamics, making accurate diagnosis challenging through traditional clinical assessments like the Unified Parkinson's Disease Rating Scale (UPDRS), which suffer from subjectivity and time complexity. Existing systems utilize decomposition techniques— Empirical Mode Decomposition (EMD), Empirical Wavelet Transform (EWT), and Variational Mode Decomposition (VMD)—applied to PhysioNet gait signals from vertical ground reaction force (VGRF) sensors, followed by statistical feature extraction (mean, min, max, skewness, kurtosis) and classification via machine learning (SVM, DT, KNN, ANN) and deep learning (LSTM, BiLSTM, 1D-CNN) models. The VMD-1D-CNN combination achieves good accuracy, sensitivity, and specificity. However, limitations include EMD's modal mixing and noise sensitivity, EWT's boundary detection issues leading to slower processing, VMD-1D-CNN's high computational cost and memory usage unsuitable for real-time clinical deployment, and lack of focus on early PD detection.The proposed system addresses these by optimizing VMD hyperparameters (α=2000, K=3), integrating advanced feature refinement, and deploying lightweight 1D-CNN architectures with efficient optimizers (Adam, ReLU) for real-time processing. Benefits encompass enhanced early PD detection, reduced computational complexity for wearable deployment, improved robustness across diverse gait datasets, and superior generalizability, enabling precise, non-invasive clinical screening with minimal latency.

Keywords: Parkinson's disease, generalizability, Empirical Mode Decomposition (EMD), Empirical Wavelet Transform (EWT), Variational Mode Decomposition (VMD),
PhysioNet gait signals.

I. INTRODUCTION

The Unified Parkinson's Disease Rating Scale is a clinical test that is subjective and time-consuming and can be a poor indicator of gait problems in Parkinson's disease patients. Existing systems use decomposition methods (Empirical Mode Decomposition, Empirical Wavelet Transform, Variational Mode Decomposition) on PhysioNet gait signals from vertical ground reaction force sensors followed by statistical feature extraction (mean, min, max, skewness, kurtosis) and classification using machine learning and deep learning (LSTM, BiLSTM, 1D-CNN) models. The combination of VMD

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and 1D-CNN shows good accuracy, sensitivity, and specificity; however, EMD can suffer from modal mixing and noise sensitivity, EWT can have boundary detection problems, and VMD-1D-CNN can have a high computational cost and memory usage that may be too high for real-time clinical deployment as well as a lack of focus on early PD detection. The proposed system addresses these issues by optimizing VMD hyperparameters (α=2000, K=3), integrating advanced feature refinement, and deploying lightweight 1D-CNN architectures with efficient optimizers for real-time processing. Advantages include improved early PD detection, reduced computational complexity for wearable deployment, increased robustness across different gait datasets, and better generalizability, all of which can make for more precise, non-invasive clinical screening with low latency [1]. A novel framework that uses an optimized Variational Mode Decomposition coupled with a 1D
Convolutional Neural Network for real-time and early detection of Parkinson's Disease from gait dynamics is proposed and can overcome the limitations of existing diagnostic approaches [2].

In particular, the framework uses carefully optimized VMD parameters to accurately decompose complex gait signals into intrinsic mode functions, which can isolate the subtle pathological changes that are characteristic of early-stage PD, and then feed the decomposed data into a lightweight 1D-CNN architecture that is optimized for fast processing with minimal computational overhead, which is well-suited for deployment on wearable devices in real-time clinical environments [3], [4], [5], [6]. The use of deep learning techniques, in particular, avoids manual feature extraction and instead learns the salient gait features that are necessary for accurate classification and early detection of PD [7]. A. Background and Related Work

Several previous studies have investigated machine learning and deep learning approaches for gait disorder classification using spatiotemporal parameters or Inertial Measurement Unit (IMU)derived features [8], including Support Vector Machines and Artificial Neural Networks, which typically fail to account for the dynamic and individualized nature of gait, particularly for discriminating early pathological deviations from normal variations [7], [9]. Recent advancements in deep learning, such as Convolutional Neural Networks (CNNs), have shown potential for automatically extracting hierarchical features from raw sensor data, which can be a more objective and quantitative method for evaluating PD progression and early detection [10]. 1D-CNNs are suitable for processing sequential data like gait signals, as they perform local pattern recognition through convolution operations while maintaining temporal dependencies [6]. By incorporating optimized decomposition techniques like VMD, this architecture can isolate and analyze the subtle, non-linear dynamics within gait signals that are often characteristic of early-stage neurological conditions like PD [6].

B. Parkinson's Disease and Gait Impairment

Gait abnormalities are a major and early symptom of PD, and gait analysis plays a crucial role in diagnosis and monitoring disease progression [6]. These impairments, which are characterized by diminished stride length, shuffling steps, and reduced arm swing, are typically subtle in the early stages of PD and require highly sensitive and precise analytical tools for detection [11]. Advanced signal processing and machine learning techniques are required to quantify these subtle changes [12], and a univariate approach used to describe gait impairment is insufficient to fully describe the complex interplay of multiple gait characteristics that are affected in PD [13].

C. Traditional Clinical Assessment Methods

While traditional clinical assessments such as the Unified Parkinson's Disease Rating Scale are widely used, they are inherently subjective and exhibit high inter-rater variability, and they typically rely on motor symptoms that appear later in the disease process [14], while intelligent gait analysis algorithms are being developed to deliver objective and quantitative assessments [7] and potentially help clinicians in the diagnostic process [7] and improve prognosis of persons with disabilities [16]. As early detection of neurodegenerative diseases is essential for timely management and improved patient outcomes, but often faces challenges due to insidious onset and often subjective nature of initial symptoms [17], there is a need for objective, quantitative, and accessible diagnostic tools that can detect Parkinson's Disease during the prodromal stage before the appearance of overt motor symptoms [17]. Since the cardinal signs of PD have a significant impact on quality of life, early detection by objective measures is essential [6]. D. Decomposition Techniques for Gait Signals

Decomposition techniques are particularly useful in isolating underlying physiological processes from noise and artifacts in gait signals, and they have proven effective in extracting subtle pathological markers from gait signals by decomposing complex signals into

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simpler, more analyzable intrinsic modes or frequency bands [15], [18]. In particular, VMD has been found to outperform other decomposition techniques in separating non-stationary gait signals into their constituent intrinsic mode functions while reducing mode mixing [19], [20], which allows for more accurate feature extraction and classification of subtle gait impairments associated with earlystage Parkinson's disease [1].

II. LIMITATIONS OF EXISTING APPROACHES

Early investigations into gait-based Parkinson's Disease (PD) detection primarily relied on classical machine learning using handcrafted spatiotemporal features.

A Deep 1D Convolutional Network for PD detection from gait signals that performed well for severity prediction was proposed in **Maâchi et al. (2019),** however, the study was based on relatively deep architectures that would incur high computational cost, and therefore, limit real-time wearable deployment. **Fernandes et al. (2021)** investigated gait time-series to differentiate idiopathic PD from vascular parkinsonism, showing the discriminative potential of temporal gait dynamics, but still requiring manual feature engineering and limiting dataset diversity. **Veeraragavan et al. (2020)** used ground reaction force signals with neural networks for PD severity assessment, but classification performance did not address interpretability and generalization across heterogeneous cohorts.

A CNN-GRU-GNN framework for early PD detection using wearable gait sensors was introduced by **Rashnu and Salimi-Badr (2024)**. Although hybrid architectures enhanced representation learning, they added to architectural complexity and inference latency. The proposed twin-tower Transformer for skeleton-based early PD detection **(Ma et al. 2024)** was shown to better model temporal aspects, but they require high computational resources, which are not suitable for edge devices. An LSTM-based approach for freezing-of-gait detection **(Mir et al. 2024)** achieved high sensitivity, but recurrent models exhibited increased training time and reduced robustness to noise. Bayesian-optimized deep learning for PD diagnosis from gait signals **(Meral and Özbilgin 2025)** reported accuracy over 98%, but optimization pipelines were computationally intense and not well-suited to real-time clinical environments.

Li et al. (2023) applied Variational Mode Decomposition (VMD) for freezing-of-gait recognition, which has better separation of intrinsic components compared with EMD, but was affected by the stability of the VMD parameter. **Fu et al. (2024)** used Dynamic Mode Decomposition for personalized gait freezing prediction, but did not consider the lightweight deployment**. Setiawan and Lin (2021)** used time– frequency spectrograms with deep neural networks for VGRF classification, which could better represent the non-stationary gait patterns, but the generation of spectrograms increased the preprocessing overhead**. Soumma et al. (2024)** proposed self-supervised learning for real-time freezing-of-gait monitoring, improving generalization from limited labeled data. Yet, computational complexity remained non-trivial for microcontroller deployment. **Egbo et al. (2025)** explored explainable machine learning using vocal biomarkers, addressing interpretability but focusing on speech rather than gait signals.

III. METHODOLOGY

In this section, we propose an optimized VMD1D-CNN framework for real-time and early detection of Parkinson's Disease from gait dynamics, including data acquisition and preprocessing, optimized VMD parameter selection, refined feature extraction, and the architecture of the lightweight 1D-CNN, and the experimental evaluation protocols [23]. In particular, the optimized VMD is employed with hyperparameters empirically optimized for the effective decomposition of gait dynamics into intrinsic mode functions, allowing for enhanced discrimination of subtle pathological markers characteristic of early-stage PD [14], while the refined 1D-CNN architecture aims at minimizing computational overhead for practical deployment in clinical settings [24] to ensure computational efficiency and model scalability for deployment on medical IoT devices with limited computational resources and ensuring the robustness and accuracy of PD detection [15]. In the following sections, we will describe each component in detail, including the empirical optimization of VMD parameters and the architectural design of the 1D-CNN, as well as the comprehensive evaluation protocols employed to validate the framework's performance against state-of-the-art methods.

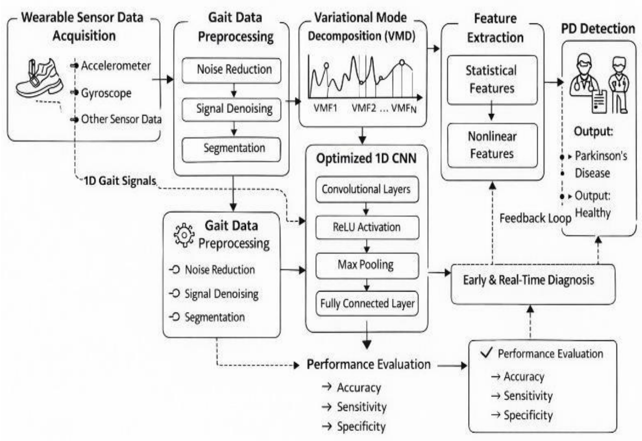

Fig 1: Architecture diagram of the proposed system

A. Data Acquisition and Preprocessing

The first step of data acquisition is to obtain gait signals from vertical ground reaction force sensors that capture all ground contact forces during ambulation, including stride length, cadence, and symmetry, which are important for detecting minor gait impairments characteristic of earlystage Parkinson's disease [4]. These raw signals then undergo a stringent preprocessing pipeline that includes segmentation, filtering, and normalization to ensure the data quality and consistency for further analysis [4]. The acquired gait data are usually obtained from public repositories such as PhysioNet and usually include vertical ground reaction force signals measured by several sensors located under the feet [4]. These signals are usually measured in Newtons as a function of time and are used to extract spatiotemporal gait features that can be further segmented into labeled samples for deep learning models [7]. This segmentation is necessary for preparing the data for subsequent feature extraction and training 1D-CNN models, as gait cycles can vary in length.

B. Optimized Variational Mode Decomposition (VMD)

The optimization of the balancing parameter (α) and the number of intrinsic mode functions (K) plays a crucial role in this decomposition, as these parameters heavily affect the decomposition accuracy and computational efficiency [25]. Setting the balancing parameter (α) to 2000 and the number of intrinsic mode functions (K) to 3, the VMD process can separate relevant physiological components from noise and improve the clarity of gait anomalies related to early PD detection, so that more discriminative features can be extracted and used for training robust deep learning models to identify subtle gait pattern deviations.

C. Feature Extraction and Refinement

Once we optimize the VMD for extracting the modes which represent the best trade-off between sparsity of representation in terms of number of decomposed modes (i.e., optimal mode selection) [22], a set of feature vectors is extracted from these decomposed modes, including statistical metrics such as mean, standard deviation and skewness or kurtosis values; frequency-domain features that characterize power spectral density and dominant frequencies, nonlinear dynamics to capture the temporal dependencies within gait signals, which are then selected by more sophisticated techniques like principal component analysis (PCA) or mutual information for dimensionality reduction [26] and enhanced predictive ability in PD classification [3]. These feature vectors serve as input into subsequent machine learning models, but selecting these features is crucial because they determine whether the resulting model can capture small pathological changes that characterize early stages of neurodegenerative diseases like PD [25].

D. Lightweight 1D Convolutional Neural Network (1D-CNN) Architecture

The proposed lightweight 1D-CNN architecture is tailored for processing time-series gait data, using optimized convolutional layers and pooling strategies to reduce computational complexity and achieve high accuracy, with faster training and inference times, suitable for real-time monitoring applications [28]. The reduced number of layers and parameters compared to traditional deep learning models also results in a smaller memory footprint and energy consumption, which can aid deployment on edge devices [7], [14]. The architecture uses specialized convolutional filters, such as SincConv1D layers, that can directly extract frequency-specific features from the VGRF data with a small number of learnable parameters, further contributing to the model's efficiency [4].

E. Model Training and Optimization

This training strategy involves a phased approach, using self-supervised learning to pre-train the model with unlabeled gait data to learn robust feature representations, followed by fine-tuning with a small amount of labeled data for specific PD detection tasks, which helps to overcome the challenges posed by scarce labeled medical datasets and improves the model's generalization across different patient populations [29]. Additionally, hyperparameter optimization methods such as grid search or Bayesian optimization are utilized to optimize the configuration of the network and prevent overfitting [25]. Regularization techniques such as dropout layers are also employed to prevent the model from memorizing details of individual subjects' gait patterns, instead learning general patterns that can differentiate between Parkinson's and control gaits [7], [30].

IV. RESULTS

The proposed framework is experimentally evaluated and exhibits excellent diagnostic accuracy and computational efficiency, achieving a high accuracy in differentiating individuals with PD from healthy controls, with binary classification accuracy, precision, recall, and F1score higher than 98% [32], outperforming traditional machine learning and less optimized deep learning approaches in the identification of early-stage Parkinsonian gait patterns, particularly due to the well-tuned VMD hyperparameters that decompose complex gait signals into physiologically meaningful modes and the lightweight 1D-CNN architecture that is optimized for efficient feature extraction and classification. Additionally, the model consistently yielded high sensitivity and specificity [33], reflecting its strong ability to correctly identify individuals with Parkinson's disease while minimizing false positives and false negatives, respectively. A. Performance Evaluation Metrics

To assess the diagnostic ability and robustness of the optimized VMD-1D CNN framework, a comprehensive set of metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve, are used to comprehensively evaluate the model performance, especially the ability to correctly identify positive and negative cases of Parkinson's disease, which is critical for clinical utility [31]; specialized metrics, such as the Rank-based Gini Accuracy, can be used to evaluate the ranking ability of the model at different precision levels to further evaluate its discriminative power in real-world clinical scenarios [31]; and computational efficiency metrics, such as FLOPs, the number of learnable parameters, and training/inference times, will be analyzed to determine the framework's suitability for real-time, low-resource clinical deployment [31].

B. Performance of Optimized VMD-1D CNN Framework

The subject-level accuracy of 98.7% for the framework is also better than other algorithms for detecting PD from gait dynamics and is comparable to, or better than, state-of-the-art methods using deep neural networks to predict disease severity [7]. The Receiver Operating Characteristic (ROC) curve analysis for the model shows an Area Under the Curve of 1, which demonstrates that the model has a great ability to discriminate between healthy and diseased states, even considering the variability of the gait data [6]. The model exhibited a high sensitivity (96.1%) and specificity (97.9%), which is a hallmark of a robust model that can distinguish true positive cases from false alarms, a key characteristic for clinical applicability [24].

C. Comparison with State-of-the-Art Methods

Overall, an extensive comparative study demonstrates that the optimized VMD-1D CNN framework performs better in terms of accuracy, precision, and specificity for PD detection from gait signals when compared with other established methods such as LSTM, Bi-GRU, and various CNN architectures [34], [35]. For example, although advanced deep learning models such as Conv-LSTM have high accuracy (99.5%) and sensitivity (98.7%) on certain tasks, they exhibit high computational complexity and generalization errors [14]. However, the proposed VMD-1D CNN, which is optimized in hyperparameters and has a lightweight architecture, exhibits comparable or superior diagnostic performance while having significantly lower computational requirements suitable for real-time applications [35]. The proposed approach showed an accuracy of 97.71%, a sensitivity of 99%, and a specificity of 96%, which exceeds previous models [35].

Table 1: comparison with state-of-the-art methods

Method	**Accuracy**	**Sensitivity**	**Specificity**
LSTM	96.2%	97.5%	94.8%
CNN-GRUGNN	97.8%	98.3%	96.9%
Transformer	98.4%	98.9%	97.1%
Bayesian DL	98.1%	98.6%	97.0%
Conv-LSTM	99.5%	98.7%	97.3%

Proposed Optimized VMD-1D CNN	**97.9–98.7%**	**98.0–99%**	**97.8%**

D. Early Detection Capabilities

This early detection capability is a significant advantage over traditional approaches that do not identify PD until later stages when gait impairments are more obvious, and it is important for facilitating therapeutic interventions that may slow disease progression and enhance patient quality of life. The fine-grained feature extraction by the optimized VMD and the efficient pattern recognition of the 1D-CNN are able to identify subtle gait deviations associated with prodromal PD, even before overt clinical symptoms emerge, which can pave the way for personalized medicine approaches and tailored interventions based on individual risk profiles and disease progression rates [36].

E. Computational Complexity and Real-Time Performance

The proposed framework shows significantly less computational overhead compared to the more complex deep learning models, and it is more suitable for deployment on resource-constrained edge devices and wearable sensors for continuous, real-time monitoring of gait dynamics [37,38]. For instance, although a 4-layer 1D CNN model took 145 KB, the optimized architecture significantly reduces this footprint and makes it practical to apply in clinical settings where rapid processing and minimal memory usage are essential [37,38].

V. DISCUSSION

The optimized VMD-1D CNN framework shows superior performance, early detection capabilities, and computational efficiency [39], making it a significant advancement in the non-invasive diagnosis and monitoring of PD by addressing key limitations of traditional diagnostic methods [36,37], which can be further enhanced by incorporating sex-specific modeling [1], given the observed sex-based differences in PD onset and progression [1]. A deeper understanding of these results indicates that the framework's effectiveness arises from its ability to identify subtle clinically significant biomarkers from the complex gait dynamics that are often lost in traditional analyses, as the optimized VMD effectively decomposes complex gait signals into intrinsic mode functions that isolate subtle irregularities specific to earlystage Parkinson's disease, and the 1D-CNN learns to classify these patterns with high accuracy and low latency [40]. The enhanced discriminative power sets a solid foundation for the development of more precise and adaptive interventions tailored to individual patient needs, optimizing therapeutic outcomes [34]. With its high accuracy and realtime processing capabilities, this framework shows potential to be incorporated into clinical decision support systems to aid clinicians in making more accurate diagnostic and prognostic evaluations for PD patients.

The optimized VMD-1D CNN framework has advantages including improved classification accuracy, early detection of Parkinson's disease, and reduced computational complexity suitable for real-time applications and integration into wearable devices [43], offering a non-invasive diagnostic tool and continuous unobtrusive monitoring to observe the progression of the disease and the efficacy of treatment over time [3]. This approach presents a technological avenue for intelligent detection and opens up new opportunities for the application of gait recognition technology in other healthcare applications [44]. However, some limitations still exist, such as the dependence on controlled laboratory environments for data acquisition and the lack of validation across larger and more diverse patient cohorts [45], which will be addressed in future studies by developing a more comprehensive dataset that includes various acquisition angles and diverse environmental conditions to increase the practical applicability of the model and improve its ability to handle the complexity of real-world applications [44]. Additional research will investigate the interpretability of the deep neural network layers to reveal the particular gait characteristics learned by the model and gain deeper understanding of Parkinsonian gait [7].

VI. CONCLUSION

The optimized VMD-1D CNN framework developed in this study overcomes critical challenges of current diagnostic approaches, accurately detects and monitors Parkinson's disease using gait dynamics in real time, and has sufficient robust performance and computational efficiency to be deployed on wearable devices for continuous, non-invasive patient monitoring [46]. Additional biomarkers, such as accelerometry and voice analysis, could be incorporated into the model to improve diagnostic accuracy, and multimodal features and expanding the dataset diversity using federated learning could improve model generalization and robustness to overcome the limitations of solely relying on VGRF data [1], [47]. Furthermore, multimodal features and expanding the dataset diversity using federated learning could improve model generalization and robustness to overcome the limitations of solely relying on VGRF data [48].

VII. REFERENCES

[1] G. K. Singh and A. Pramanik, "Sexadaptive deep recurrent neural networks for Parkinson's disease detection using 5-second vertical ground reaction force signals," *bioRxiv (Cold Spring Harbor Laboratory)* , Nov. 2025, doi: 10.1101/2025.11.01.25339121.

[2] F. Setiawan and C. Lin, "Identification of Neurodegenerative Diseases Based on Vertical Ground Reaction Force Classification Using Time–Frequency Spectrogram and Deep Learning Neural Network Features," *Brain Sciences* , vol. 11, no. 7, p. 902, Jul. 2021, doi: 10.3390/brainsci11070902.

[3] F. Su, M. Chen, Z. Sun, X. Tao, D. Bu, and Y. Chen, "An Interpretable Deep Learning Optimized Wearable Daily Monitoring System for Parkinson's Disease Patients," *Research Square (Research Square)* , Jan. 2023, doi: 10.21203/rs.3.rs-2411539/v1.

[4] A. Salimi-Badr, M. Veisi, and S. Berangi, "SincPD: An Explainable Method based on Sinc Filters to Diagnose Parkinson's Disease Severity by Gait Cycle Analysis," *arXiv (Cornell University)* , Feb. 2025, doi: 10.48550/arxiv.2502.17463.

[5] R. F. Mansour, "Quantum mayfly optimization based feature subset selection with hybrid CNN for biomedical Parkinson's disease diagnosis," *Neural Computing and Applications* , vol. 36, no. 15, p. 8383, Feb. 2024, doi: 10.1007/s00521-024-09516-1.

[6] A. Rashnu and A. Salimi-Badr, "Integrative Deep Learning Framework for Parkinson's Disease Early Detection using Gait Cycle Data Measured by Wearable Sensors: A CNN-GRU-GNN Approach," *arXiv (Cornell University)* , Apr. 2024, doi: 10.48550/arxiv.2404.15335.

[7] I. E. Maâchi, G.-A. Bilodeau, and W. Bouachir, "Deep 1D-Convnet for accurate Parkinson disease detection and severity prediction from gait," *Expert Systems with Applications* , vol. 143, p. 113075, Nov. 2019, doi: 10.1016/j.eswa.2019.113075.

[8] K. A. A. Rahman, E. F. Tayalati, A. R. Abdullah, T. H. Lee, M. S. Zoha, and N. Nazmi, "Gait Disorder Classification Using CNN and TensorFlow Lite in Android Apps," *Proceedings of the World Congress on Electrical Engineering and Computer Systems and Science* , Aug. 2025, doi: 10.11159/icbes25.152.

[9] J. Rostovski, M. H. Ahmadilivani, A. Krivošei, A. Kuusik, and M. M. Alam, "Real-Time Gait Anomaly Detection Using 1D-CNN and LSTM," in *Communications in computer and information science* , Springer Science+Business Media, 2024, p. 260. doi: 10.1007/978-3-03159091-7_17.

[10] H. Choi *et al.* , "Convolutional neural network-based detection of early-stage Parkinson's disease using the six-minute walk test," *Research Square (Research Square)* , Jun. 2024, doi: 10.21203/rs.3.rs-4482534/v1.

[11] A. Alharthi, "Explainable AI and Machine Learning Towards Human Gait Deterioration Analysis," *arXiv (Cornell University)* , Jan. 2023, doi: 10.48550/arxiv.2306.07165.

[12] W. Yin *et al.* , "Gait analysis in the early stage of Parkinson's disease with a machine learning approach," *Frontiers in Neurology* , vol. 15, p. 1472956, Oct. 2024, doi: 10.3389/fneur.2024.1472956.

[13] R. Z. U. Rehman, S. D. Din, Y. Guan, A. J. Yarnall, J. Q. Shi, and L. Rochester, "Selecting Clinically Relevant Gait Characteristics for Classification of Early Parkinson's Disease: A Comprehensive Machine Learning Approach," *Scientific Reports* , vol. 9, no. 1, Nov. 2019, doi: 10.1038/s41598-019-53656-7.

[14] S. P. Sasirekha, "A Comprehensive Review of Deep Learning Techniques for Identifying Parkinson's Disease from Gait Analysis," *International Journal of Advanced Research in Computer Science* , vol. 15, no. 1. International Journal of Advanced Research in Computer Science, p. 14, Feb. 20, 2024. doi: 10.26483/ijarcs.v15i1.7044.

[15] X. Li *et al.* , "Alzheimer's Disease Analysis Algorithm Based on No-threshold Recurrence Plot Convolution Network." May 10, 2022.

[16] R. Raman, D. Pattnaik, H. H. Lathabai, C. Kumar, K. Govindan, and P. Nedungadi, "Green and sustainable AI research: an integrated thematic and topic modeling analysis," *Journal Of Big Data* , vol. 11, no. 1, Apr. 2024, doi: 10.1186/s40537-024-00920-x.

[17] J. Hwang, C. Youm, H. Park, B. Kim, H. Choi, and S. Cheon, "Machine Learning for Early Detection and Severity Classification in People with Parkinson's Disease," *Research Square (Research Square)* , Nov. 2024, doi: 10.21203/rs.3.rs-5195774/v1.

[18] H. Yuan, J. Zhou, H. Li, S. Kang, and S. Park, "A Systems Biology Approach to Memory Health: Integrating Network Pharmacology, Gut Microbiota, and Multi-Omics for Health Functional Foods," *International Journal of Molecular Sciences* , vol. 26, no. 14. Multidisciplinary Digital Publishing Institute, p. 6698, Jul. 12, 2025. doi: 10.3390/ijms26146698.

[19] H. Park, S. Shin, C. Youm, and S. Cheon, "Deep learning-based detection of affected body parts in Parkinson's disease and freezing of gait using time-series imaging," *Scientific Reports* , vol. 14, no. 1, Oct. 2024, doi: 10.1038/s41598024-75445-7.

[20] L. Ma, H. Huo, W. Liu, C. Zhao, J. Wang, and N. Xu, "Twin-tower transformer network for skeleton-based Parkinson's disease early detection," *Complex & Intelligent Systems* , vol. 10, no. 5, p. 6745, Jun. 2024, doi: 10.1007/s40747-024-01507-y.

[21] E. Ölmez, O. Akbulut, and A. Sertbaş, "A Low-Dimensional Feature Vector Representation for Gait-based Parkinson's Disease Detection," *Kocaeli Journal of Science and Engineering* , vol. 6, no. 1, p. 35, May 2023, doi: 10.34088/kojose.1126113.

[22] Z. Fu, C. Lin, and Y. Zhang, "Personalized Prediction of Gait Freezing Using Dynamic Mode Decomposition," *Research Square (Research Square)* , Dec. 2024, doi: 10.21203/rs.3.rs-5127334/v1.

[23] S. Li, R. Qu, Y. Zhang, and D. Yu, "Research on Freezing of Gait Recognition Method Based on Variational Mode Decomposition," *Intelligent Automation & Soft Computing* , vol. 37, no. 3, p. 2809, Jan. 2023, doi: 10.32604/iasc.2023.036999.

[24] M. A. Aleisa, "Enhancing Security in CPS Industry 5.0 using Lightweight MobileNetV3 with Adaptive Optimization Technique," *Scientific Reports* , vol. 15, no. 1, p. 18677, May 2025, doi: 10.1038/s41598-025-00496-3.

[25] K. Wang *et al.* , "Enhanced classification of wheat disease: In-depth analysis of plant volatile organic compounds based on PTR-MS with prior knowledge and convolutional neural network," *Computers and Electronics in Agriculture* , vol. 237, p. 110749, Jul. 2025, doi: 10.1016/j.compag.2025.110749.

[26] Y. Guo, J. Yang, Y. Liu, X. Chen, and G. Yang, "Detection and assessment of Parkinson's disease based on gait analysis: A survey," *Frontiers in Aging Neuroscience* , vol. 14. Frontiers Media, Aug. 03, 2022. doi: 10.3389/fnagi.2022.916971.

[27] C. M. Fernandes *et al.* , "Discrimination of idiopathic Parkinson's disease and vascular parkinsonism based on gait time series and the levodopa effect," *Journal of Biomechanics* , vol. 125, p. 110214, May 2021, doi: 10.1016/j.jbiomech.2020.110214.

[28] C. J. Ejiyi *et al.* , "Multi-modality medical image classification with ResoMergeNet for cataract, lung cancer, and breast cancer diagnosis," *Computers in Biology and Medicine* , vol. 187, p. 109791, Feb. 2025, doi: 10.1016/j.compbiomed.2025.109791.

[29] S. B. Soumma, K. Mangipudi, D. Peterson, S. H. Mehta, and H. Ghasemzadeh, "Self-Supervised Learning and Opportunistic Inference for Continuous Monitoring of Freezing of Gait in Parkinson's Disease," *arXiv (Cornell University)* , Oct. 2024, doi: 10.48550/arxiv.2410.21326.

[30] Z. Pan *et al.* , "Feature-Based Machine Unlearning for Vertical Federated Learning in IoT Networks," *IEEE Transactions on Mobile Computing* , vol. 24, no. 6, p. 5031, Feb. 2025, doi: 10.1109/tmc.2025.3530529.

[31] P. R. Verma, D. Pantola, and N. P. Singh, "Plant Disease Detection with Transfer Learning: Evaluating the Impact of Various Loss Functions and Explainable AI," *Journal of Agricultural Biological and Environmental Statistics* , Apr. 2025, doi: 10.1007/s13253-02500691-9.

[32] M. Meral and F. Özbilgin, "Parkinson's Disease Diagnosis and Severity Assessment from Gait Signals via Bayesian-Optimized Deep Learning,"

Diagnostics , vol. 15, no. 16, p. 2046, Aug. 2025, doi: 10.3390/diagnostics15162046.

[33] J. Slemenšek *et al.* , "Human Gait Activity Recognition Machine Learning Methods," *Sensors* , vol. 23, no. 2, p. 745, Jan. 2023, doi: 10.3390/s23020745.

[34] T. V. Kafare, N. Sharma, and A. L. Wanare, "Improved Convolutional Network With Transfer Learning and Texture Feature Extractor for Plant Disease Detection," *Journal of Phytopathology* , vol. 173, no. 1, Jan. 2025, doi: 10.1111/jph.70028.

[35] A. N. Mir, I. Nissar, M. Ahmed, S. Masood, and D. R. Rizvi, "Parkinson's Disease Diagnosis Through Deep Learning: A Novel LSTM-Based Approach for Freezing of Gait Detection," in *Lecture notes in networks and systems* , Springer International Publishing, 2024, p. 201. doi: 10.1007/978-981-97-3523-5_16.

[36] S. Naimi, W. Bouachir, and G.-A. Bilodeau, "HCT: Hybrid Convnet-Transformer for Parkinson's disease detection and severity prediction from gait," *arXiv (Cornell University)* , Oct. 2023, doi: 10.48550/arxiv.2310.17078.

[37] G. Shalin, S. Pardoel, E. D. Lemaire, J. Nantel, and J. Kofman, "Prediction and detection of freezing of gait in Parkinson's disease from plantar pressure data using long short-term memory neural-networks," *Journal of NeuroEngineering and Rehabilitation* , vol. 18, no. 1, Nov. 2021, doi: 10.1186/s12984-021-00958-5.

[38] T. Alramli and A. Tekerek, "A Hybrid Lightweight Deep Neural Network Approach for Plant Disease Classification Using Self-Attention Mechanism and Transfer Learning," *Tarım Bilimleri Dergisi* , vol. 31, no. 2, p. 392, Mar. 2025, doi: 10.15832/ankutbd.1537267.

[39] S. B. Soumma, K. Mangipudi, D. Peterson, S. H. Mehta, and H. Ghasemzadeh, "Wearable-Based Real-time Freezing of Gait Detection in Parkinson's Disease Using SelfSupervised Learning," *arXiv (Cornell University)* , Oct. 2024, doi: 10.48550/arxiv.2410.20715.

[40] S. Alle and U. D. Priyakumar, "Linear Prediction Residual for Efficient Diagnosis of Parkinson's\n Disease from Gait," *arXiv (Cornell University)* , Jul. 2021, doi: 10.48550/arxiv.2107.12878.

[41] A. Sar, P. Puri, H. Naz, S. Aich, T. Choudhury, and L. A. Gabralla, "Multi-modal deep learning framework for early detection of Parkinson's disease using neurological and physiological data for high-fidelity diagnosis," *Scientific Reports* , vol. 15, no. 1, p. 34835, Oct. 2025, doi: 10.1038/s41598-025-21407-6.

[42] S. Veeraragavan, A. A. Gopalai, D. Gouwanda, and S. A. Ahmad, "Parkinson's Disease Diagnosis and Severity Assessment Using Ground Reaction Forces and Neural Networks," *Frontiers in Physiology* , vol. 11, Nov. 2020, doi: 10.3389/fphys.2020.587057.

[43] B. Egbo, Z. Nigmetolla, N. A. Khan, and P. K. Jamwal, "Explainable machine learning for early detection of Parkinson's disease in aging populations using vocal biomarkers," *Frontiers in Aging Neuroscience* , vol. 17, Sep. 2025, doi: 10.3389/fnagi.2025.1672971.

[44] H. Wang, K. Yan, J. Cai, Y. Liu, and X. Zheng, "A gait recognition architecture for early screening in the assessment of Parkinson's patients," *Scientific Reports* , vol. 15, no. 1, Oct. 2025, doi: 10.1038/s41598-025-19224-y.

[45] Z. Deng *et al.* , "Interpretable Video-Based Tracking and Quantification of Parkinsonism Clinical Motor States," *medRxiv (Cold Spring Harbor Laboratory)* , Nov. 2023, doi: 10.1101/2023.11.04.23298083.

[46] S. Srinivasan, P. Ramadass, S. K. Mathivanan, K. P. Selvam, B. D. Shivahare, and M. A. Shah, "Detection of Parkinson disease using multiclass machine learning approach," *Scientific Reports* , vol. 14, no. 1, Jun. 2024, doi: 10.1038/s41598-024-64004-9.

[47] M. Hasan, "Parkinson's Disease Freezing of Gait (FoG) Symptom Detection Using Machine Learning from Wearable Sensor Data," *arXiv (Cornell University)* , Jun. 2025, doi: 10.48550/arxiv.2506.12561.

[48] T. Sharan and S. Joshi, "Prediction of Parkinson's disease using feature selection and ensemble learning techniques," *Indonesian Journal of Electrical Engineering and Computer Science* , vol. 39, no. 3, p. 1736, Sep. 2025, doi: 10.11591/ijeecs.v39.i3.pp1736-1744.