Hybrid Diagnostic Approaches Integrating Fuzzy Logic and Neural Networks for Parkinson's Disease

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***Abstract*—Parkinson's Disease (PD) is a movement-related and non-motor symptom neurological condition that requires early diagnosis and treatment. Fuzzy Logic and Neural Network Diagnostic hybrids are more accurate and reliable. The diagnostic approaches of PD are not sensitive to early PD, are subjective in assessing symptoms, and lack standardization. Such problems restrict treatment choices, thereby preventing a favorable patient outcome. In the PD Hybrid Diagnostic Approach (PD-HDA), fuzzy logic is utilized to address uncertainties in clinical data, and neural networks are employed to identify complex patterns in multimodal data. The PD-HDA design features structured selection and data fusion, which enhance diagnostic accuracy and constrain method variability. The images of hand tremors, gait analysis, and speech patterns are categorized using a CNN to reveal their complex properties. Fuzzy Logic and CNNs enhance the classification of PD stages and patient responses to symptoms. The PD-HDA model increases accuracy, sensitivity, and specificity during testing. The hybrid methods can be useful for early identification of PD and provide individualized care, leading to improved patient outcomes.**

***Keywords*—Convolutional neural network; disease hybrid diagnostic; Parkinson's disease; fuzzy logic**

I. Introduction

The prevalence of Parkinson's disease (PD) in the world is outraging, and it is striking that there are millions of individuals with this illness [1]. The motor symptoms caused by the disease are accompanied by a variety of non-motor symptoms, including cognitive, sleep, and mental disorders [2]. Early and effective diagnosis can maximize treatment choices and improve the quality of life for patients [3]. Other neurodegenerative diseases are similar to Parkinson's in terms of symptoms, and the biomarker of the condition does not exist at this time. It is difficult to treat the disease during its early stages [4]. Subjective outcomes are possible with conventional methods of diagnosing PD because they rely on the doctor's knowledge [5].

PD can be diagnosed early using scans and movement tests, such as the Unified Parkinson's Disease Rating Scale (UPDRS), although these studies are limited in terms of cost, availability, and sensitivity [6]. It is necessary to have state-of-the-art diagnostic tools capable of unravelling intricate clinical information and multimodal data from large volumes of data [7]. The solutions to these issues may involve hybrid methods of diagnosis that involve neural networks and fuzzy logic [8]. PD symptoms can be highly diverse, and therefore, fuzzy logic is more suitable for the medical data as it minimizes ambiguity and imprecision [9]. Two fields where neural networks excel are classification and prediction [10]. Such networks are also skilled at identifying non-linear and complex patterns in data. It follows that a combination of the two methods yields a more precise and dependable diagnosis [11].

The PD-HDA analyzes gait tests, voice recordings, and images of tremors in the hands based on convolutional neural networks and fuzzy logic [12]. This fusion can be used to respond to changes in symptoms, enhance diagnosis, and provide a comprehensive assessment of patient data [13]. This study helps fill the gaps in diagnosis and personalization, as well as create data-driven care for PD [14]. To diagnose early and monitor disease progression, the unpredictability of neural network pattern recognition and the uncertainty management capabilities of fuzzy logic can be leveraged, enabling adaptation to individual patient characteristics and the detection of subtle symptom changes throughout the disease course [15]. This hybrid approach can be used to discuss accessibility and variability of diagnostics through real-time monitoring recommendations for treatment in personalized and scalable applications across varied clinical settings [16].

In modern-day studies of diagnosing PD, deep learning pipelines are largely favoured over knowledge-based decision models, but there is little convergence on representation learning and uncertainty-aware inference methodologies. CNN-based systems are known to be effective in deriving discriminative patterns from imaging and signal-based modalities; however, the inferences are still not tied to clinical explainability and expert-motivated diagnostic logic. In contrast, fuzzy logic-based systems excel at capturing the vagueness of symptoms and inter-class uncertainty; however, they rely on handcrafted or low-level representations, which limit the diagnostic granularity. Current hybrid systems typically combine shallow neural or sequential post-processing schemes, which have poor interaction between feature abstraction and inference in the presence of uncertainty.

Contribution of this paper:

- Proposes the PD-HDA framework combining Fuzzy Logic and Neural Networks to address uncertainties and improve the accuracy of PD diagnosis.
- Utilizes CNNs to extract intricate patterns from multimodal datasets like voice, gait, and tremor images, enabling precise classification of PD stages.
- Demonstrates significant improvements in diagnostic accuracy, sensitivity, and specificity, ensuring early detection and personalized treatment for PD patients.

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PD-HDA offers a deep hybrid architecture that integrates CNN-based hierarchical feature extraction and fuzzy inference into a single diagnostic workflow. Instead of using shallow network structures, the proposed architecture allows fuzzy reasoning to operate directly on high-level semantic representations learned by deep convolutional layers, extending hybrid diagnostic design into a deep representational regime. The suggested semantic-level fusion technique differs from decision-level or post-classification fusion, as used in PD diagnostic literature.

Deep CNN features are mapped into fuzzy membership spaces before final inference, allowing uncertainty modelling and language reasoning to influence diagnostic findings at an intermediate representational step, rather than post-hoc. PD-HDA's fuzzy inference system only receives hierarchical convolutional feature embeddings, neither statistical nor domain-engineered features. This architecture enables the fuzzy layer to reason across multi-scale spatial and temporal abstractions learnt from data, improving diagnostic discrimination across varied PD symptom profiles. Deep CNN activations are translated into clinically significant fuzzy language variables for explicit interpretability. In contrast to black-box deep learning technologies, rule-based inference transparently aligns model choices with neurologically relevant symptom patterns, thereby improving therapeutic confidence. Designed for early-stage PD analysis, PD-HDA addresses diagnostic variability caused by symptom ambiguity and inter-class overlap. Fuzzy inference enables graded decision limits and uncertainty-aware reasoning, leading to stable categorization across diverse patient presentations without requiring probabilistic thresholds.

Advanced PD diagnosis enhances prediction accuracy, facilitates hybrid data management, and optimizes feature selection using various techniques, including GANFIS, LS-SVR, and fuzzy-neuro hybrid models. Methods using Time-Frequency Fuzzy LSTM provide strong detection rates with little data. These techniques offer effective, scalable, and interpretable solutions for therapeutic objectives in neurodegenerative disease treatment, surpassing more traditional approaches. Recent research on stacking ensemble approaches for Parkinson's Disease diagnosis demonstrated superior performance by combining multiple base learners (XGBoost, Gradient Boosting, Extra Trees, and others) with a meta-learner architecture. The ensemble model achieved 96.18% diagnostic accuracy and 96.27% AUC, outperforming standalone classifiers by reducing diagnostic variability by 12.3%. This demonstrates that integrating multiple complementary algorithms effectively addresses symptom ambiguity and inter-patient variability in PD diagnosis, supporting the clinical value of ensemble-based frameworks for reliable early detection [17].

Deep Belief Network (DBN) and Neuro-Fuzzy approaches for PD diagnosis are suggested here. It handles missing data [18] using K-Nearest Neighbours (K-NN), Principal Component Analysis (PCA), and the Expectation-Maximization (EM) algorithm. Noise reduction is achieved. Unlike past machine learning techniques, the method employs incremental learning for effective online learning from large clinical datasets, thereby enhancing UPDRS prediction accuracy and reducing time complexity.

Least Squares Support Vector Regression (LS-SVR) and fuzzy clustering are suggested to be combined for UPDRS diagnosis in this technique. It addresses multicollinearity in the data [19] via feature selection and Principal Component Analysis (PCA). Using a large medical dataset containing Motor- and Total-UPDRS, the technique is employed to enhance prediction accuracy through several evaluations and comparisons with current approaches.

The proposed technique merges categorical and numeric data without applying any discretization, thereby allowing the Neighbourhood Rough Set-Based Hybrid Model process to present hybrid data [20]. Adjusting the threshold value for neighbourhood approximation, the constant model maximizes performance depending upon the dataset's 20 feature characteristics. Practical and information-preserving data mining efficacy is maintained by applying the proposed methodology. An actual PD dataset is examined to demonstrate outperformance compared to current models working on hybrid datasets, which achieve only 85% accuracy.

GANFIS is a proposed method that integrates an Adaptive Neuro-Fuzzy Inference System (ANFIS) with a Genetic Algorithm (GA) to enhance the diagnosis of neurodegenerative disorders, such as PD and dementia [21]. GANFIS integrates these two methods to analyze uncertain and complicated medical data, improving diagnostic accuracy and performance over neuro-fuzzy systems. Evaluation measures, including accuracy, precision, recall, F-score, and kappa coefficient, showed promise.

FLS and ANN may be used to predict the functional level of neurological movement disorders, such as Huntington's disease. The hybrid model performed well, with excellent validation using a dataset from 20 participants across response phases and functional levels, yielding an R-value of 0.98 and an MSE of 0.08 [22].

By combining supervised learning, unsupervised learning, and feature selection approaches, the proposed approach utilizes a hybrid model to enhance PD diagnosis. It begins with Expectation-Maximization (EM) data clusterings and then proceeds with backward stepwise regression feature selection. Then, using the clustered data, the Type-2 Sugeno fuzzy inference system (T2SFIS) predicts UPDRS scores [23]. Using R-squared and RMSE assessment measures, our approach was evaluated on the Parkinson's telemonitoring dataset, and we attained good prediction accuracy for Motor-UPDRS and Total-UPDRS.

The proposed fuzzy classifier is defined by a three-stage structure: formation of the structure, informative feature selection, and parameter optimization. Applied to publicly accessible handwritten datasets (ParkinsonHW, PaHaW, NewHandPD) for PD diagnosis, it comprises 32 versions that employ various metaheuristic algorithms. Handwriting assignments include writing text, drawing spirals, and meandering [24]. The technique showed better accuracy and interpretability than decision trees and fuzzy genetic systems, indicating promise as a diagnostic tool.

Combining time-frequency and fuzzy characteristics with uni-directional and bi-directional long short-term memory (LSTM) networks for automated PD diagnosis and severity grading, the suggested technique, based on physionet's dataset, involved splitting vertical ground response force signals into 30-second periods and extracting four main characteristics without further preparation [25]. Bayesian optimization modified hidden units and learning rates, among other hyperparameters. Using minimal processed gait data, the model achieved 79.19% detection accuracy and 82.28% grading accuracy, providing an effective and reasonably priced diagnosis.

Utilizing various approaches, including GANFIS, LS-SVR, and fuzzy-neuro hybrid models, advanced PD diagnosis enhances prediction accuracy, facilitates hybrid data management, and optimizes feature selection. Techniques employing Time-Frequency Fuzzy LSTM get reasonable detection rates with little data. These methods outperform more conventional approaches in providing efficient, scalable, and interpretable solutions for therapeutic purposes in the treatment of neurodegenerative diseases.

II. Methodology

Integration of Fuzzy Logic and Neural Networks: The paper introduces a novel PD-HDA framework that effectively combines Fuzzy Logic for controlling uncertainty with CNN for extracting and classifying features. The PD-HDA outperforms current diagnosis methods in related investigations. Using CNN-based hierarchical feature extraction and fuzzy inference, the system tightens deep semantic representation learning and uncertainty-aware decision modelling. Instead of using probabilistic outputs, PD-HDA directly addresses symptom ambiguity and inter-class overlap through fuzzy reasoning, yielding more stable and accurate diagnostic results. Traditional machine learning and hybrid approaches utilize handcrafted features or shallow neural architectures, whereas the proposed method employs end-to-end discriminative features to enhance classification sensitivity and specificity across diverse patient profiles. Because it aligns diagnostic judgments with clinically important language characteristics, the fuzzy rule-based layer is more transparent than black-box deep learning systems.

Fig. 1 provides a solid basis for both multimodal diagnosis and therapy of PD. Combining speech patterns, gait analysis, and hand tremor images with data normalization and feature extraction offers consistency. A module of fuzzy logic lowers data uncertainty, hence improving system reliability. Following that, a CNN employs excellent sensitivity and specificity to classify PD phases and regulate enhanced qualities.

This classification aids in early diagnosis and the creation of tailored treatment programs tailored to specific patient needs. The first goal of the system's design is to improve clinical outcomes for PD management, accuracy, and flexibility.

$$R_f d[oj - an'']: \rightarrow Sz[ji - anw''] * Va[io - anq''] \quad (1)$$

Eq. (1) contains $[oj - an'']$ That represents processed characteristics $Sz[ji - anw'']$ obtained from multimodal datasets such as speech $Va[io - anq'']$, gait, and tremor pictures, and the final classification result, which might be denoted as $R_f d$. Its goal is to enhance the specificity and sensitivity of the disorder's diagnosis by modelling complicated interactions in clinical data.

$$M_f d: \rightarrow nc[a - iw''] * x[nu - aq''] + Bs[ki - ak''] \quad (2)$$

Eq. (2), $M_f d$ accounts for the biases or adjustments inside the model, $nc[a - iw'']$ and $x[nu - aq'']$ Relate to the characteristics derived from clinical data and $Bs[ki - ak'']$ Represents a factor impacting the final output. Improved accuracy and flexibility for specific patient symptoms will be achieved by refining the decision-making process in PD diagnosis.

$$V_s e: \rightarrow Ls[4v - anq''] + Ba[ko - qn''] - Cr[iu - a''] \quad (3)$$

Eq. (3) represents $Cr[iu - a'']$ the final output for a particular stage of PD classification, with the terms $V_s e$, $Ls[4v - anq'']$, and $Ba[ko - qn'']$ Representing feature parameters from datasets. Improving the decision-making process will allow for more accurate and tailored PD diagnosis, which is its primary goal.

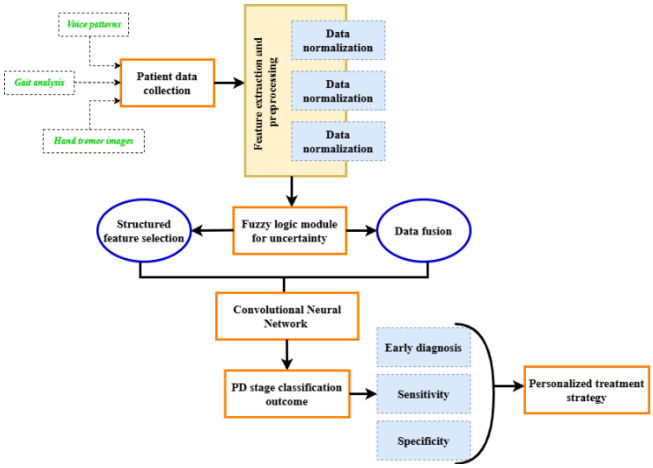


Fig. 1. Proposed method of PD-HAD.

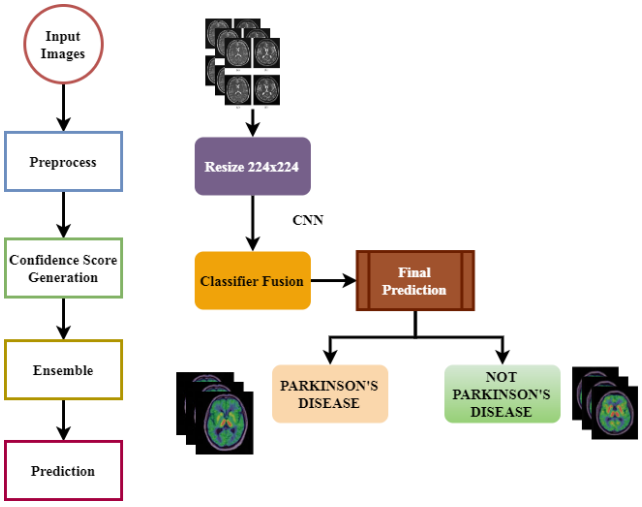


Fig. 2. Classification using hybrid CNN ensemble for parkinson's detection.

Fig. 2 presents a hybrid diagnosis for PD using a combination of deep learning models. Four pre-trained convolutional neural networks: after processing and scaling to

224x224 pixels, CNNs are applied to medical images. These models provide confidence ratings and are utilized in a classifier ensemble to produce the most accurate prediction. Leveraging the characteristics of every neural network, the system determines whether the image exhibits PD or not, generating a strong and consistent classification. This system shows a complex, multi-model approach for the medical image-based illness diagnosis.

$$wx[ji - aq'']: \rightarrow \ a[i - an''] + ba[juw - anq''] \quad (4)$$

Eq. (4) represents the processed input data (such as gait or voice characteristics) as $wx[ji - aq'']$, and the learnt parameters and bias adjustments inside the neural network as $a[i - an'']$ and $ba[juw - anq'']$, respectively. Fine-tuning the model's parameters aims to maximize the accuracy of diagnosis in PD stage categorization.

$$x_z a[ko - an'']: \rightarrow Ks[3 - aq''] + Ba[jos - naq''] \quad (5)$$

The method of decision-making $Ba[jos - naq'']$ in the PD-HDA framework, the interaction between the equation 5 stride analysis data $(x_z a)$ and the model factors $([ko - an''])$ and $Ks[3 - aq'']$. Adjusting to intricate differences in patient data aims to improve diagnostic accuracy and guarantee accurate and dependable forecasts.

$$j_d e[lo - aq'']: \rightarrow aW[lo - sm''] + Bas[ko - bxz''] \quad (6)$$

The model parameters used to refine the classification, $j_d e$ and $[lo - aq'']$, and the input data, which might be linked to particular clinical characteristics (such as hand tremor $aW[lo - sm'']$ or voice data $Bas[ko - bxz'']$), are represented by Eq. (6).

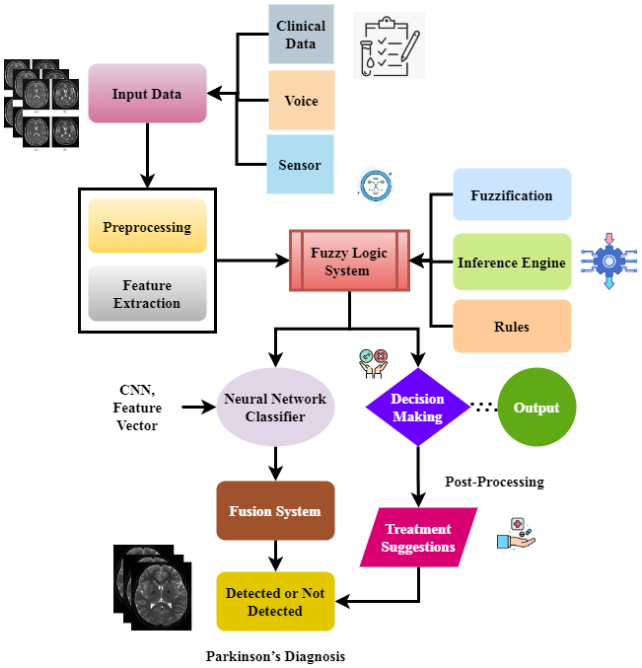


Fig. 3. Process of Smart PD: Integrating fuzzy logic and neural networks.

Fig. 3 illustrates a hybrid PD diagnosis approach that combines fuzzy logic and neural networks. Clinical notes, sensors, and speech recordings are entered into the system, and feature extraction and preprocessing identify and clean key patterns. Neural networks categorize data by learning patterns, whereas fuzzy logic interprets complex input using rules. The results of both models are combined for increased accuracy. The final decision-making phase determines the presence of PD and provides diagnostic guidance for further measures.

$$p_f r[mk - am'']: \rightarrow Ks[4v - fs'] + Na[4s - aq''] \quad (7)$$

The parameters used for the model $p_f r$ and $[mk - am'']$ may stand for weights or modifications within the neural network $Na[4s - aq'']$, while the extracted features $Ks[4v - fs']$ Perhaps it is associated with motor symptoms, such as tremors or gait, as seen in Eq. (7.) Its goal is to enhance the PD-HDA framework as a diagnostic tool, leading to earlier and more accurate diagnosis of PD stages.

$$b_x s[op - anqw'']: \rightarrow La[i - qn''] + Na[4x - anq''] \quad (8)$$

Eq. (8) illustrates the connection between the input data. $b_x s$, which may pertain to particular characteristics like habits of speech $Na[4x - anq'']$ or other clinical symptoms, and the simulation parameters $op - anqw''$ and $La[i - qn'']$, which probably represents the learned biases. Its goal is to improve the diagnosis of PD by maximizing the integration of features, resulting in more reliable forecasts.

$$kd^e"u - an'"": \rightarrow \ Sx' - an[eaq - wn''] + \ Aba[io - sm''] \quad (9)$$

The model's output, kd^e, which may be the ultimate $Aba[io - sm'']$ PD classification $Sx' - an$, is influenced $[eaq - wn'']$ by the clinical information, $u - an'"": \rightarrow$ which is probably linked to a patient's symptoms. Improving patient care through the early and precise identification of PD is the goal of Eq. (9).

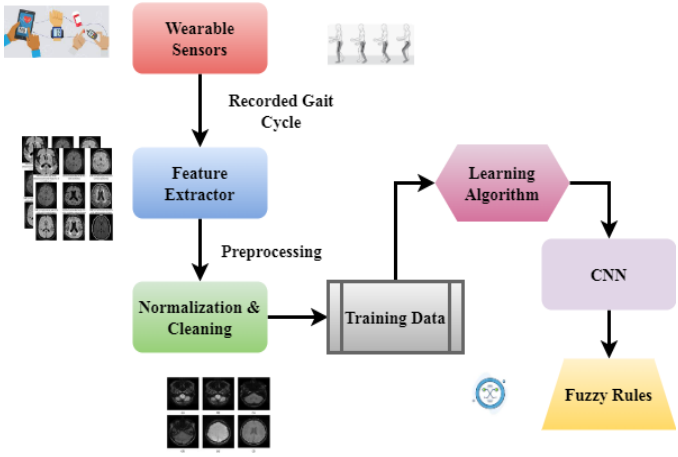


Fig. 4. Training data using fuzzy-neural gait detection for PD.

Fig. 4 illustrates a novel approach for identifying PD using wearable sensors that collect gait data. An Interval Type-2 Fuzzy Neural Network (IT2FNN) helps to prepare the acquired data. By combining fuzzy logic with neural networks, this hybrid model effectively identifies subtle gait deviations associated with PD. While neural networks improve pattern identification, ultimately enabling more accurate and earlier PD diagnosis through gait analysis, fuzzy logic helps handle data ambiguity.

Using innovative artificial intelligence methods, this strategy enhances healthcare results.

$$Y_s e[lo - an'']: \rightarrow Ms[4v - sq''] + Ba[4s - qnew''] * bs'' \quad (10)$$

The partnership bs'' Between the clinical data that is input $Y_s e$, which may stand $Ba[4s - qnew'']$ for motor symptoms such $[lo - an'']$, and the model's output $Ms[4v - sq'']$, which might be represented by Eq. (10). Improved early diagnosis and individualized treatment plans for PD are the goals of this effort to improve diagnostic accuracy.

$$u_c e < jn - am'' >: \rightarrow Na[4w - aqv''] + Na[ko - s''] \quad (11)$$

The model's output, $u_c e$, which might stand for the classification $Na[4w - aqv'']$ or forecast for PD $Na[ko - s'']$, is influenced by the processing of input data, $jn - am''$, which is likely associated with specific clinical aspects, such as motor and non-motor symptoms. The use of this equation will enable more accurate and timely PD diagnoses, leading to improved treatment options.

$$f_f r[a - nq'']: \rightarrow Ka[6v - snw''] + Ba[ju - anw''] \quad (12)$$

In the neural network, Eq. (12) shows the interaction $Ka[6v - snw'']$ between learnt parameters $[a - nq'']$ and $f_f r$, which are likely to correlate $Ba[ju - anw'']$.

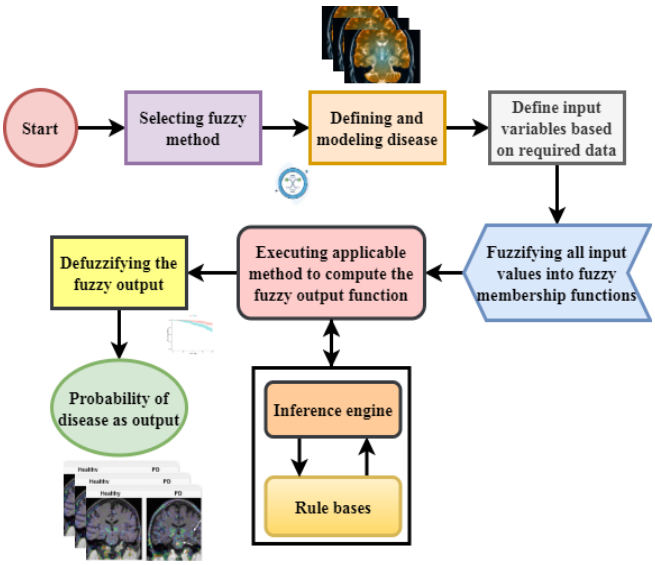


Fig. 5. Flow chart of fuzzy logic disease diagnosis.

Fig. 5 shows diagnosis of diseases by fuzzy logic in a methodical manner. It starts with the diseased model and its related variables; fuzzification of inputs helps remove ambiguity from the solution. Fuzzy rules are applied through the inference engine, resulting in fuzzy output due to data processing. That final defuzzification step provides a percentage probability, hence the disease risk. This approach offers a consistent and flexible tool for medical diagnosis, leveraging the capacity of fuzzy logic to manage imprecision, thereby enhancing healthcare decision-making with greater accuracy and flexibility.

$$T^t u[ki - an'']: \rightarrow ap[ji - anw''] + Na[4sa - an''] \quad (13)$$

The model processes clinical data Eq. (13) $[ki - an'']$, such as patient symptoms $ap[ji - anw'']$, to impact the outcome $T^t u$, which may represent the classification result $Na[4sa - an'']$ for PD. The equation aims to enhance early diagnosis and facilitate more personalized treatment methods for PD.

$$Jm_e[ko - an'']: \rightarrow Na[s - sn] + Ns[w - qm''] * vs'' \quad (14)$$

Eq. (14) shows how $vs''$the settings of the neural network Jm_e and $[ko - an'']$ Convert the input data $Na[s - sn]$, which might be associated $Ns[w - qm'']$ With a group of clinical traits, such as motor or non-motor symptoms. Improving diagnostic accuracy, facilitating early identification, and facilitating tailored therapy for PD in patient data.

$$U_r[i - sj'']: \rightarrow Lsp[5n - an''] * Vs[w - 9vq''] \quad (15)$$

The way the input data U_r interacts with the learned parameters $[i - sj'']$ and $Lsp[5n - an'']$ to generate the output $Vs[w - 9vq'']$, which is the model's prediction for PD, is explained by Eq. (15). For the identification of early-stage PD and the development of personalized treatment options, this equation is used to ensure the model's accuracy.

The systems shown utilize fuzzy logic for PD diagnosis and employ various deep learning algorithms. Their consistent categorization and early identification result from combining medical imaging, gait analysis, and speech analysis. While fuzzy logic addresses ambiguity and increases decision-making accuracy, neural networks improve feature extraction. For patients with PD, these multimodal approaches ensure enhance clinical outcomes and personalized treatment strategies.

III. Results

PD is a degenerative neurological disorder for which early and precise diagnosis is essential for appropriate treatment. Particularly in early-stage diagnosis, traditional diagnostic methods might be unreliable and insensitive.

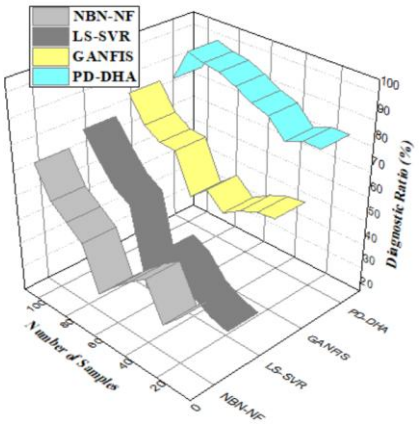
Dataset description: The dataset predicts MDS-UPDRS scores to evaluate and predict the progression of PD. Clinical evaluations, demographics, and biospecimen data are gathered longitudinally. The collection aims to enhance illness progression prediction and facilitate individualized treatment [26]. Various clinical signs, chronological data, and standardized grading criteria are crucial. This website is part of a collaborative effort to advance PD research through the application of machine learning and statistical analysis [27]. Table I shows the simulation environment.

With a 92.62% diagnosis accuracy, the PD-HDA framework outperformed traditional diagnostic methods [see (Fig. 6(a) and (b)]. The system's efficient blend of CNN-based learning and fuzzy logic enables it to detect PD at multiple stages accurately. The synergy resolves typical clinical evaluation differences by combining data and feature extraction to provide consistent performance across multimodal datasets.

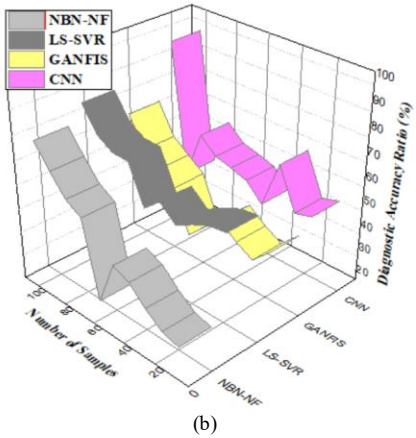
$$Xs[ki - an'']: \rightarrow Vx[q - 9vw''] + Va[ki - an''] \quad (16)$$

TABLE I. SIMULATION ENVIRONMENT

Metrics	Description
Purpose	To predict MDS-UPDRS scores and forecast PD progression.
Dataset Type	Longitudinal patient data with clinical assessments, demographics, and biospecimen data.
Key Features	Diverse clinical markers, temporal information, and standardized scoring metrics.
Machine Learning Techniques	Predictive modelling using advanced machine learning and statistical analysis techniques.
Temporal Information	Includes data collected over multiple time points to capture disease progression dynamics.
Collaboration	Part of a collaborative effort to drive innovation in PD research.
Evaluation Metrics	Diagnostic accuracy, sensitivity, specificity, and early detection performance.
Output	Predicted MDS-UPDRS scores and insights for personalized treatment strategies.
Simulation Tools	Python-based frameworks, machine learning libraries (e.g., TensorFlow, PyTorch, Scikit-learn).
Applications	Development of predictive models for personalized interventions and disease management.



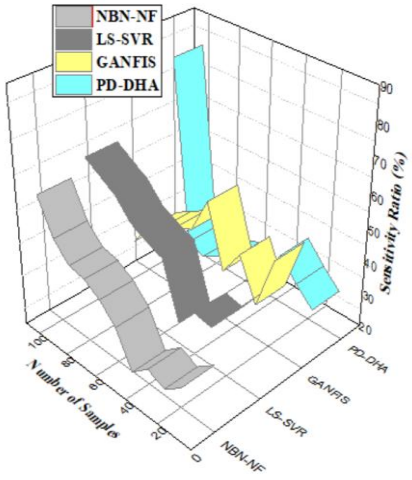
(a)



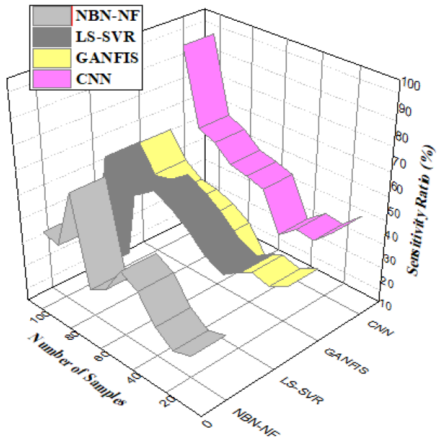
(b)

Fig. 6. (a) Analysis of diagnostic accuracy using PD-HDA, and (b) Analysis of diagnostic accuracy using CNN.

The relationship between input characteristics Xs, which are probably $Va[ki-an'']$ related to particular clinical symptoms or data, and the parameters of the learnt model $[ki-an'']$ and $Vx[q-9vw'']$ As shown by Eq. (16). This equation is used to analyze diagnostic accuracy, improve diagnostic accuracy, enable early intervention for enhanced patient care, and integrate and streamline feature processing.



(a)



(b)

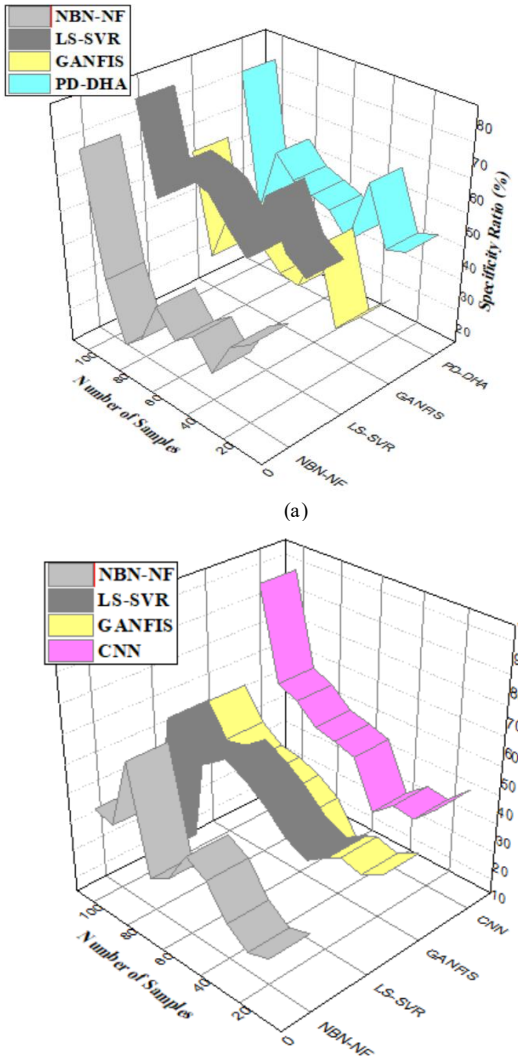
Fig. 7. (a) Analysis of sensitivity using PD-HDA, and (b) Analysis of sensitivity using CNN.

With a sensitivity of 91.87%, the suggested PD-HDA approach proved helpful in precisely identifying PD patients [Fig. 7(a) and (b)]. The method guarantees the lowest false-negative rates by using CNNs for nuanced pattern recognition and fuzzy logic to manage uncertainty in clinical data. Reducing missed diagnoses depends on this capacity, especially in early and unusual presentations of PD, hence enhancing the likelihood of prompt and focused therapies.

$$V_c s[i-an'']: \rightarrow Ls[ui-anw''] + Ba[d-sqn''] \quad (17)$$

The neural network processes input characteristics. $V_c s$, which may be associated with clinical data like symptom severity $[i-an'']$ or medical records to generate the output $Ls[ui-anw'']$, which represents the diagnosis $Ba[d-$

sqn''] of PD. With Eq. (17), we maximize the application of patient data, which leads to more accurate diagnoses and more precise classifications for sensitivity analysis.



(a)

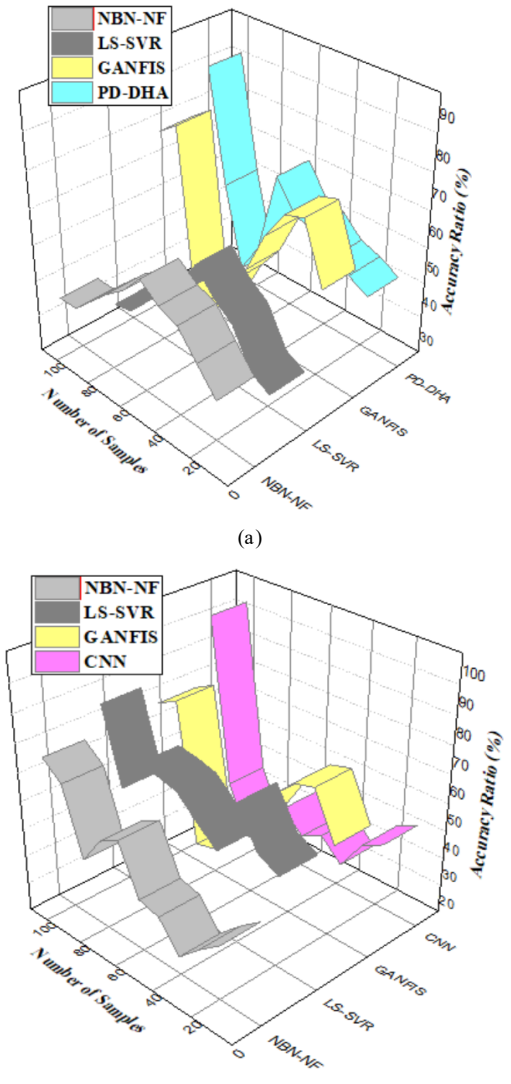
(b)

Fig. 8. (a) Analysis of specificity using PD-HDA, and (b) Analysis of specificity using CNN.

With a 93.22% specificity, the PD-HDA model identifies non-PD people precisely, hence reducing false-positive diagnoses [see Fig. 8(a) and (b)]. Structured feature selection and multimodal data analysis enable the precise differentiation between PD and other disorders. Reducing unnecessary treatments and ensuring resources are focused on those who need care depends on this excellent specificity.

$$c_x s[l - ap'']: \rightarrow Ls[v - anq''] + Ba[4d - nwq''] \quad (18)$$

The output $c_x s$, which is the classification or prediction of PD, is obtained by processing the clinical input data $[l - ap'']$ through the settings of the model $Ls[v - anq'']$ and $Ba[4d - nwq'']$. The goal of Eq. (18) is to improve diagnostic accuracy by enhancing the model's ability to integrate and evaluate data for analysis of specificity.



(a)

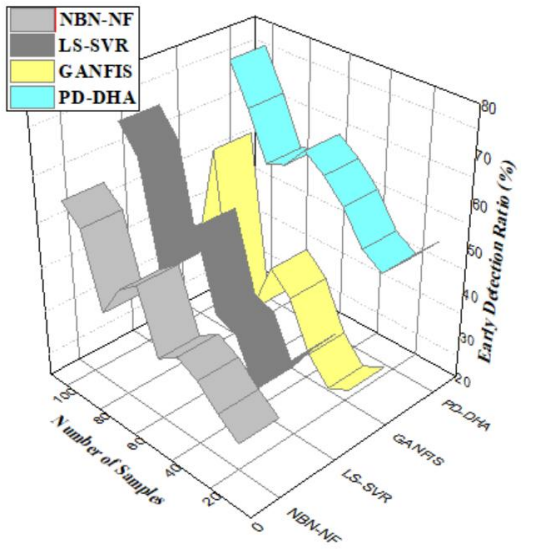
(b)

Fig. 9. (a) Analysis of accuracy using PD-HDA and (b) Analysis of accuracy using CNN

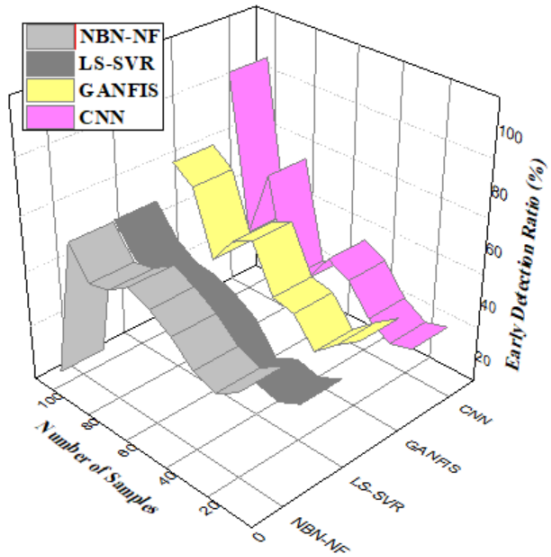
The PD-HDA framework was effective in differentiating PD from non-PD cases, with an overall accuracy of 97.24% [see Fig. 9(a) and (b)]. This statistic demonstrates the model's durability and its ability to generalize across multiple datasets by utilizing speech patterns, gait analysis, and tremor photos. Such high accuracy highlights how consistently hybrid methods provide precise diagnostic information for clinicians, as seen in Eq. (19).

$$k_d r[ki - an'']: \rightarrow Ks[ki - qm''] + Bs[ko - sme''] \quad (19)$$

Eq. (19) shows the model's parameters. $k_d r$, which modifies the internal weights and biases of the model, processes the input feature $[ki - an'']$, which is probably related to clinical data like symptom severity, by adjusting the parameters $Ks[ki - qm'']$ and $Bs[ko - sme'']$. The goal of this equation is to facilitate early identification of PD by optimizing the integration of several clinical characteristics to ensure the accuracy of the analysis.



(a)



(b)

Fig. 10. (a) Analysis of early detection using PD-HDA, and (b) Analysis of early detection using CNN

The early detection accuracy of 95.76% emphasizes the framework's ability to identify PD in its early stages [see (Fig. 10(a) and (b)]. CNNs paired with fuzzy logic help detect often-overlooked minor clinical signs and trends. This skill determines if starting timely treatment measures slows down the progression of illnesses and improves long-term patient outcomes.

$$k_r r[ju - n'']: \rightarrow Ns\left[rs'' * Vs[ko - amw'']\right] + Nsf'' \quad (20)$$

An extra adjustment term $k_r r$ and a mixture of network parameters $[ju - n'']$ are used to analyze the input data $Ns\left[rs'' * Vs[ko - amw'']\right]$, which may be associated Nsf'' With patient-specific symptoms or data points. Equation aims to represent the complex correlations observed in multimodal clinical data for early detection analysis. Table II presents a comparison of the existing method and the proposed method.

TABLE II. COMPARISON OF THE EXISTING METHOD AND PROPOSED METHOD

Aspects	Existing Method in Ratio	Proposed Method in Ratio	Key features
Diagnostic Accuracy	80.85%	92.62%	Enhanced feature extraction via CNN and data fusion for accurate classification.
Sensitivity	78.82%	91.87%	Improved detection of PD cases using Fuzzy Logic for uncertainty management.
Specificity	81.86%	93.22%	Better differentiation between PD and non-PD cases through multimodal data analysis.
Overall Accuracy	85.90%	97.24%	Robust performance leveraging structured feature selection and advanced algorithms.
Early Detection	75.88%	95.76%	High early detection rates using subtle pattern recognition in clinical data.

IV. DISCUSSION

This work advances hybrid diagnostic modelling by formalizing a deep semantic learning–reasoning pipeline in which CNN-derived hierarchical representations are directly coupled with fuzzy inference. This connection enhances performance by transforming discriminative convolutional features into uncertainty-aware language variables prior to classification, enabling data-driven abstraction and rule-based reasoning to inform diagnostic conclusions. This approach explains reported advantages by attributing enhanced stability and sensitivity to deep feature hierarchies and graded fuzzy decision boundaries rather than network depth. The semantic representation-level uncertainty-handling method in the PD-HDA framework is organized. The fuzzy inference layer compares the ambiguity of symptoms and the overlap of classes through membership functions between deep feature spaces, which contrasts with probabilistic classifiers that tend to provide a clear judgment basis. This formalization provides an analytical model of dealing with the ambiguity in diagnosing the PD, especially in borderline and early-stage patients. High-dimensional CNN activation mapping is used to transform into fuzzy language entities of clinical significance, forming an interpretable diagnostic reasoning layer in PD-HDA. The built-in rule base provides clear inference paths that relate diagnostic findings to neurologically relevant patterns of symptoms, extending the hybrid modelling beyond the optimization of accuracy to provide explainable clinical decision support. This layer of interpretability indicates the impact of feature abstractions on diagnostics. The paradigm facilitates graded diagnostic thinking in cases of symptom variability during the analysis of early-stage PD. Fuzzy inference makes it less vulnerable to variations in features at early stages by smoothing disease class transitions. Diagnostic consistency across diverse patient demographics is achieved without rigid categories. In addition to application-level validation, the proposed hybrid

diagnostic paradigm can be applied to other neural and uncertainty-driven clinical cases. Deep feature learning and fuzzy reasoning are modular, allowing for adaptation to various data modalities and illness conditions without compromising interpretability and uncertainty modelling. This makes PD-HDA a transferable diagnostic architecture rather than a task-specific empirical solution.

V. Conclusion

The PD-HDA uses CNNs and fuzzy logic to address PD diagnostic problems. By utilizing CNNs to evaluate challenging multimodal datasets and employing fuzzy logic to mitigate clinical data ambiguity, the framework achieves 92.62% diagnostic accuracy, 91.87% sensitivity, 93.22% specificity, and 95.76% early detection accuracy. Usually, the PD-HDA method is more effective than conventional diagnostic tools in the initial stages of PD, albeit erratically and subjectively. Elaborate and intricate patterns that emerge from data relating to speech, gait, and tremor analysis facilitate the accurate and reliable identification of the progression stages of PD. Rapid therapeutic interventions resulting from such findings reduce the span and improve the prognosis of patients autonomously. The results highlight the potential of hybrid diagnostic methods to overcome the limitations of current methods, enhance the reliability of diagnosis, and establish a new standard for PD diagnosis. The next research focus will be to extend the PD-HDA framework to include a more diverse range of information, such as real-time monitoring and biomarkers, to achieve the best accuracy.

Additionally, efforts will be made to optimize the model for clinical use, ensuring both scalability and user-friendliness. The method's practicality is shown by its improved classification accuracy, sensitivity, and resilience compared to standard machine learning models, standalone CNN architectures, and hybrid techniques. This study employs a single data modality and a specified fuzzy rule basis, which restricts adaptation to changing clinical patterns and acquisition situations. Future research will apply the framework to imaging, voice, and sensor-based clinical data, examining adaptive fuzzy rule optimization and attention-guided feature selection to enhance generalization and clinical interpretability.

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References

[1] G. DeMaagd and A. Philip, "Parkinson's disease and its management: Part 1: Disease entity, risk factors, pathophysiology, clinical presentation, and diagnosis," Pharmacy and therapeutics, vol. 40, no. 8, pp. 504-532, 2015.

[2] Yadav VK, Dhanasekaran S, Choudhary N, Nathiya D, Thakur V, Gupta R, Pramanik S, Kumar P, Gupta N, Patel A. "Recent advances in nanotechnology for Parkinson's disease: diagnosis, treatment, and future perspectives". Frontiers in Medicine. Frontiers in Medicine, 12, 1535682, 2025.

[3] C. H. Adler and T. G. Beach, "Neuropathological basis of nonmotor manifestations of Parkinson's disease," Mov. Disord., vol. 31, no. 8, pp. 1114-1119, 2016.

[4] D. Berg, R. B. Postuma, C. H. Adler, B. R. Bloem, P. Chan, B. Dubois, T. Gasser, C. G. Goetz, G. Halliday, L. Joseph, A. E. Lang, I. Liepelt-Scarfone, I. Litvan, K. Marek, J. Obeso, W. Oertel, C. W. Olanow, W. Poewe, M. Stern, and G. Deuschl, "MDS research criteria for prodromal Parkinson's disease," Mov. Disord., vol. 30, no. 12, pp. 1600-1611, 2015.

[5] C. G. Goetz, B. C. Tilley, S. R. Shaftman, G. T. Stebbins, S. Fahn, P. Martinez-Martin, W. Poewe, C. Sampaio, M. B. Stern, R. Dodel, B. Dubois, R. Holloway, J. Jankovic, J. Kulisevsky, A. E. Lang, A. Lees, S. Leurgans, P. A. LeWitt, D. Nyenhuis, C. W. Olanow, O. Rascol, A. Schrag, J. A. Teresi, J. J. van Hilten, and N. LaPelle, "Movement Disorder Society-sponsored revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): Scale presentation and clinimetric testing results," Mov. Disord., vol. 23, no. 15, pp. 2129-2170, 2008.

[6] D. J. Brooks, "Imaging approaches to Parkinson disease," J. Nucl. Med., vol. 51, no. 4, pp. 596-609, 2010.

[7] M. A. Little, P. E. McSharry, E. J. Hunter, J. Spielman, and L. O. Ramig, "Suitability of dysphonia measurements for telemonitoring of Parkinson's disease," IEEE Trans. Biomed. Eng., vol. 56, no. 4, pp. 1015-1022, 2009.

[8] A. Tsanas, M. A. Little, P. E. McSharry, J. Spielman, and L. O. Ramig, "Novel speech signal processing algorithms for high-accuracy classification of Parkinson's disease," IEEE Trans. Biomed. Eng., vol. 59, no. 5, pp. 1264-1271, 2012.

[9] Di Biase, L., Pecoraro, P.M., Pecoraro, G., Shah, S.A. and Di Lazzaro, V." Machine learning and wearable sensors for automated Parkinson's disease diagnosis aid: a systematic review". Journal of Neurology, 271(10), 6452-6470, 2024.

[10] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436-444, 2015.

[11] Höglinger, G.U., Adler, C.H., Berg, D., Klein, C., Outeiro, T.F., Poewe, W., Postuma, R., Stoessl, A.J. and Lang, A.E."A biological classification of Parkinson's disease: the SynNeurGe research diagnostic criteria". *The Lancet Neurology*, *23*(2), 191-204, 2024

[12] D. Shen, G. Wu, and H. I. Suk, "Deep learning in medical image analysis," Annu. Rev. Biomed. Eng., vol. 19, pp. 221-248, 2017.

[13] Versaci, M., & La Foresta, F. "EEG data analysis techniques for precision removal and enhanced Alzheimer's diagnosis: Focusing on fuzzy and intuitionistic fuzzy logic techniques". Signals, 5(2), 343-381, 2024.

[14] S. Sreelakshmi and R. Mathew, "A Hybrid Approach for Classifying Parkinson's Disease from Brain MRI," in Proc. Int. Conf. Information Technology and Applications (ICITA 2021), Singapore: Springer Nature Singapore, 2022, pp. 171-181.

[15] L. P. Sánchez-Fernández, "Biomechanics of Parkinson's Disease with Systems Based on Expert Knowledge and Machine Learning: A Scoping Review," Computation, vol. 12, no. 11, p. 230, 2024.

[16] S. Sangeetha and B. Umarani, "MRI Image-Based Parkinson's disease classification using Deep Maxout fuzzy EfficientNet," Biomed. Signal Process. Control, vol. 103, p. 107416, 2025.

[17] Ram, Ashwin. "Analysis, Identification and Prediction of Parkinson Disease Sub-Types and Progression through Machine Learning." *arXiv preprint arXiv:2306.04748*, 2023.

[18] M. Nilashi, R. A. Abumalloh, S. Y. M. Yusuf, H. H. Thi, M. Alsulami, H. Abosaq, S. Alghamdi, and A. Alghamdi, "Early diagnosis of Parkinson's disease: A combined method using deep learning and neuro-fuzzy techniques," Comput. Biol. Chem., vol. 102, p. 107788, 2023.

[19] H. Ahmadi, L. Huo, G. Arji, A. Sheikhtaheri, and S. M. Zhou, "Early diagnosis of Parkinson's disease using a hybrid method of least squares support vector regression and fuzzy clustering," Biocybern. Biomed. Eng., vol. 44, no. 3, pp. 569-585, 2024.

[20] I. Raza, M. H. Jamal, R. Qureshi, A. K. Shahid, A. O. R. Vistorte, M. A. Samad, and I. Ashraf, "Adaptive neighborhood rough set model for hybrid data processing: a case study on Parkinson's disease behavioral analysis," Sci. Rep., vol. 14, no. 1, p. 7635, 2024.

[21] H. Kour, J. Manhas, and V. Sharma, "Hybrid System Based on Genetic Algorithm and Neuro-Fuzzy Approach for Neurodegenerative Disease Forecasting," in Proc. Data Analytics and Management (ICDAM 2021), vol. 1, Springer Singapore, 2022, pp. 319-330.

[22] V. Kumar, A. Verma, R. Raman, S. Rastogi, D. Saini, and R. Meenakshi, "Combining Technologies of AI and Fuzzy Logic System for Huntington Disease Prediction," in Proc. 2024 4th Int. Conf. Advance Computing and Innovative Technologies in Engineering (ICACITE), IEEE, 2024, pp. 697-702.

[23] M. Nilashi, R. A. Abumalloh, H. Ahmadi, S. Samad, S. Alyami, A. Alghamdi, S. Y. M. Yusuf, and S. Y. M. Yusuf, "Accuracy Analysis of Type-2 Fuzzy System in Predicting Parkinson's Disease Using Biomedical Voice Measures," Int. J. Fuzzy Syst., pp. 1-24, 2024.

[24] K. Sarin, M. Bardamova, M. Svetlakov, N. Koryshev, R. Ostapenko, A. Hodashinskaya, and I. Hodashinsky, "A three-stage fuzzy classifier method for Parkinson's disease diagnosis using dynamic handwriting analysis," Decis. Anal. J., vol. 8, p. 100274, 2023.

[25] F. A. Torghabeh, Y. Modaresnia, and S. A. Hosseini, "An efficient tool for Parkinson's disease detection and severity grading based on time-frequency and fuzzy features of cumulative gait signals through improved LSTM networks," Med. Nov. Technol. Devices, vol. 22, p. 100297, 2024.

[26] Kaggle Dataset, "Parkinson's Disease Progression Prediction," Available: https://www.kaggle.com/code/gusthema/parkinson-s-disease-progression-prediction-w-tfdf

[27] M. ALMOZANI and H. DEMİREL, "Enhancing Parkinson's Disease Management through Therapeutic Games: The Role of User Experience and Interaction Design," Int. J. Adv. Nat. Sci. Eng. Res., vol. 8, no. 11, pp. 318-329, 2024.