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Fuzzy model for the classification of Parkinson's disease based on voice signals

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Abstract: This study presents a Mamdani-type fuzzy logic model for classifying Parkinson's disease (PD) based on voice signals. The model demonstrates improved performance compared to several existing methods, achieving 97.2% accuracy, 0.9696 sensitivity, 1.0 specificity, and an F-measure of 0.98. These metrics suggest that the proposed model offers higher classification precision than previous approaches. By leveraging fuzzy logic, the model enhances interpretability and addresses some uncertainties inherent in medical data. While the results are promising, further validation with more extensive and diverse datasets is necessary before the model can be integrated into clinical decision support systems for the early diagnosis of PD.

Keywords: *Parkinson's disease; fuzzy model.*

1. Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects millions of individuals worldwide. It is characterized by motor symptoms such as tremors, bradykinesia, rigidity, and non-motor symptoms, including disturbances in the sense of smell, sleep problems, depression, cognitive decline, and voice impairments [1-5]. Recent studies have shown that vocal symptoms, such as dysphonia and changes in pitch, are among the earliest indicators of PD, often preceding noticeable motor impairments [5]. Notably, approximately 90% of PD patients exhibit vocal problems in the early stages, with symptoms ranging from stuttering to deterioration in vocal quality [6, 7].

The early detection of PD is critical for managing its progression and improving patient outcomes. Traditional diagnostic methods rely heavily on clinical assessments, which are often subjective and can miss early signs of the disease. Researchers have proposed a range of non-invasive methods for early detection, including the acoustic analysis of voice signals, physiological signals, and gait analysis [2, 8, 9]. These approaches provide insights into the disease's progression and reduce the need for frequent physical clinical visits, thus easing the clinicians' workload [6]. Given the significance of vocal symptoms in PD, telemedicine studies have increasingly focused on verbal disorder-based systems [10, 11]. Speech processing, particularly the non-invasive detection of anomalies in physiological speaking, has emerged as a promising method, with features like Jitter, Shimmer, and Fundamental Frequency being pivotal in PD studies [12]. Automated tools that analyze voice signals offer a non-invasive, cost-effective method for early detection. However, many existing machine learning (ML) methods used for

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voice-based PD classification, such as Support Vector Machines (SVMs) and neural networks, suffer from a lack of interpretability, often referred to as the "black box" problem [7, 13, 14]. This limits their clinical applicability, as healthcare professionals require transparent and understandable models to inform their decisions.

In contrast, fuzzy logic provides a promising solution by combining rule-based reasoning with the ability to handle uncertainty and imprecision in medical data. A Mamdani-type fuzzy logic system, in particular, offers a transparent decision-making process through linguistic rules derived from expert knowledge. This study introduces a Mamdani-type fuzzy logic model designed to classify PD using voice signals. The model aims to address the limitations of existing ML approaches by enhancing interpretability while maintaining high classification accuracy.

The key contributions of this work are:

1. Development of a fuzzy logic model that outperforms several existing methods regarding accuracy, sensitivity, and specificity.
2. Introduction of an interpretable rule-based system that provides insights into decision-making.
3. A comprehensive evaluation of the model's performance using well-established metrics and comparisons with state-of-the-art methods.

In the following sections, we review existing literature on PD classification using voice signals, describe the methodology and design of the fuzzy logic system, and present a detailed evaluation of the model's performance in comparison to existing benchmarks.

2. Literature Review

The classification of Parkinson's Disease (PD) based on voice signals has gained increasing attention in recent years due to its non-invasive nature and potential for early detection. Several methods have been proposed, ranging from traditional machine learning (ML) algorithms to more complex deep learning approaches. However, many of these methods face limitations that reduce their clinical applicability, particularly in terms of interpretability and handling uncertainty in medical data.

2.1. Machine Learning Approaches for PD Classification

The study and classification of Parkinson's disease (PD) have been an area of extensive research. Among the multiple studies conducted, several have employed the UCI dataset for their experiments. Sakar, et al. [6] explored the applicability of the Tuneable Q-factor Wavelet Transform (TQWT) on voice signals of PD patients for feature extraction. Their study juxtaposed the efficacy of TQWT against traditional voice signal processing techniques for PD classification. The findings were promising, with TQWT outperforming other methods by achieving a peak accuracy of 0.86 using the SVM-RBF classifier on voice recordings from 252 participants, validated using the Leave-one-subject-out technique.

Akyol [15], on the other hand, ventured into deep learning, employing a Deep Neural Network (DNN) with 753 features. The dataset and specific results for this approach are detailed in the discussion section. Similarly, Xiong and Lu [16] used multiple machine learning methods, including Logistic Regression (LR), Support Vector Machines (%SVM), and Random Forests (RF). The results were validated using 10-fold cross-validation, and the best classification accuracy for all datasets was 0.76.

Another noteworthy contribution is from Grover, et al. [7], who focused on forecasting the severity of PD utilizing deep neural networks. Their method was applied to the Parkinson's Telemonitoring Voice Data Set from UCI, achieving a classification accuracy of 94.4422% for training datasets and 62.7335% for test datasets.

Zainudin, et al. [17] adopted a different approach, using radial basis function networks for PD classification. Their study was based on the UCI dataset involving 500 PD patients, and R^2 values of 0.7450 and 0.970 were found for multiple linear regression and radial basis function, respectively.

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Lastly, Hariharan, et al. [2] presented a comprehensive approach, proposing hybrid intelligent systems for PD classification. They integrated techniques like Principal Component Analysis (PCA) and linear discriminant analysis (LDA) for feature pre-processing, followed by LS-SVM, PNN, and GRNN classification. Their combined approach achieved a remarkable classification accuracy of 100% on a dataset with 31 individuals.

2.2. Fuzzy Logic in Medical Applications

In contrast, fuzzy logic systems have been used in various medical applications because they can model uncertainty and provide interpretable decisions [18-20]. Fuzzy systems allow for reasoning in the form of linguistic rules, making the decision-making process transparent. Fuzzy logic presents a distinct advantage in clinical decision-making due to its capacity to handle uncertain and vague data, often characteristic of patient symptoms [21-23]. By allowing degrees of truth rather than binary logic, fuzzy logic systems effectively interpret symptoms that are not clear-cut. This flexibility is enhanced by using linguistic "if-then" rules, which provide transparency and interpretability crucial in medical practice. Such interpretability fosters trust among clinicians, who can easily understand and validate the decision-making process [24, 25]. Moreover, fuzzy logic-based systems, especially when integrated into Clinical Decision Support Systems (CDSS), improve decision-making by combining data-driven models with expert knowledge, offering nuanced diagnoses and treatment suggestions that are easy to follow and explain [18, 20, 26].

Recent studies highlight the potential of fuzzy logic in the diagnosis of Parkinson's disease by offering a more nuanced and interpretable classification method compared to traditional machine-learning approaches. Fuzzy logic's ability to handle uncertainty and imprecise data makes it ideal for medical conditions like Parkinson's, where symptoms can be gradual, subjective, and difficult to quantify [27-30].

Despite its strengths, fuzzy logic has been underutilized in PD classification based on voice data. While fuzzy models have shown promise in handling ambiguous medical data, limited research has applied this technique to PD [27-29]. This study aims to fill this gap by developing a Mamdani-type fuzzy logic model that provides high accuracy and makes the decision process interpretable through a system of fuzzy rules.

2.3. Limitations of Existing Methods

The primary limitation of many existing machine learning approaches is their inability to offer insight into how predictions are made, which is essential for clinical trust and acceptance. Additionally, models like SVMs and DNNs often require large datasets for training, and their performance can degrade when faced with noise or uncertainty in the data. In contrast, fuzzy logic systems are inherently designed to handle such uncertainty, making them particularly suitable for medical applications where data can be noisy or incomplete.

In light of these comprehensive studies, our work aims to offer a fresh perspective, intertwining fuzzy logic to enhance the classification and understanding of Parkinson's disease through voice signals.

3. Material and Methods

The methodology used in this study follows the structured framework proposed by Hernández-Julio, et al. [20]. This framework integrates a step-by-step process for designing and implementing data-driven decision support systems, focusing on iterative development and knowledge-based rules. Below, we outline each of the relevant steps in the context of this research. For this study, more than one thousand fuzzy inference systems were developed. Ultimately, the model with the best performance (Classification accuracy) was selected, and the results were validated with that model.

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3.1. Domain Understanding and Gap Identification (Steps 1-3)

The first phase of the methodology focuses on gaining a comprehensive understanding of the problem domain, Parkinson's Disease (PD), and identifying gaps in existing voice-based classification models. An extensive literature review revealed several challenges in current PD classification approaches, such as the lack of model interpretability and the inability to handle uncertainty in the data. These limitations highlight the need for a model that is both interpretable and capable of managing data uncertainty, motivating this study's adoption of fuzzy logic.

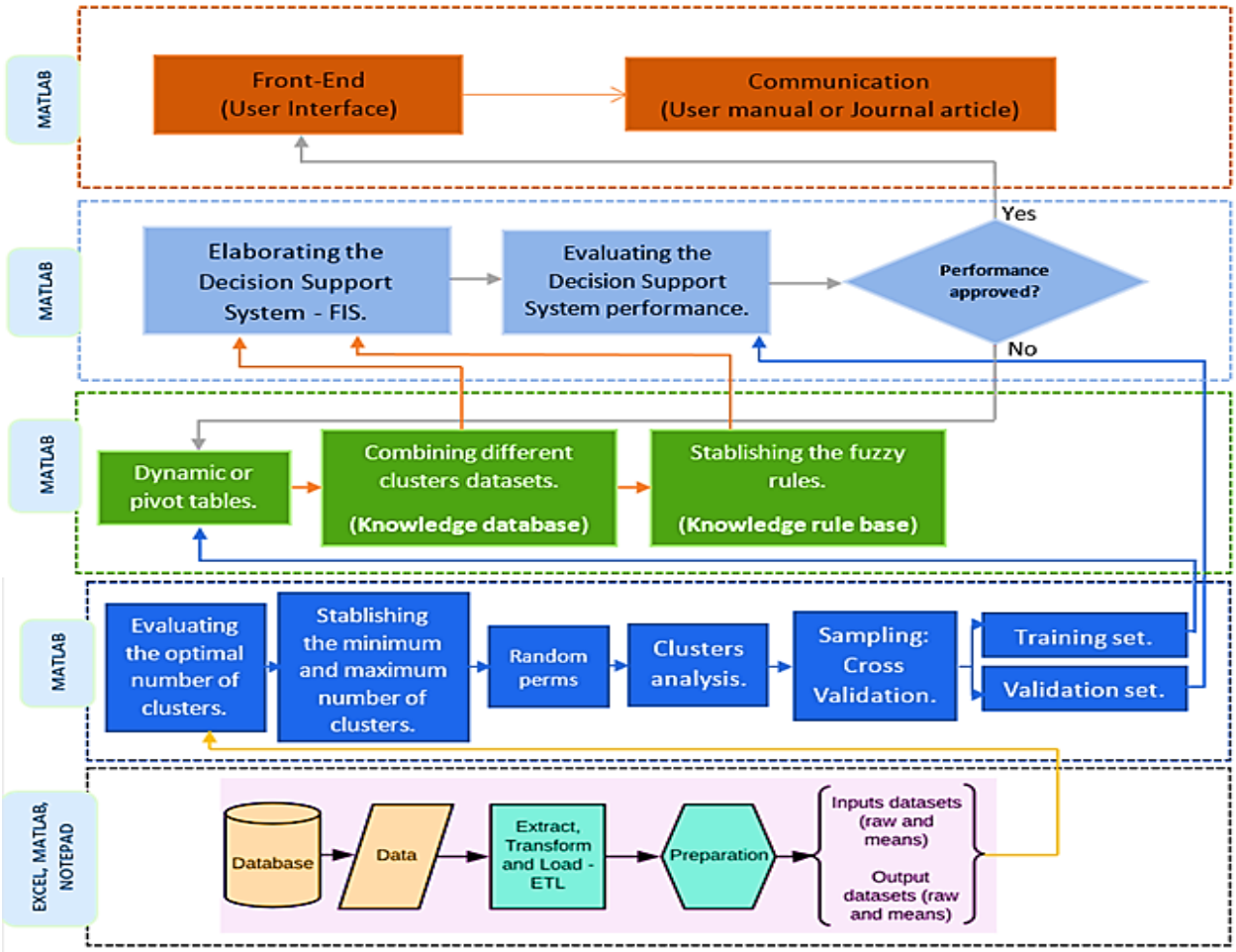

Figure 1.
The proposed five-layer architecture framework.

As illustrated in Figure 1, the framework encompasses a five-layer architecture. The entire implementation process of the Fuzzy Model is detailed in Figure 2. Consisting of eleven activity steps, the framework's comprehensive breakdown is as follows:

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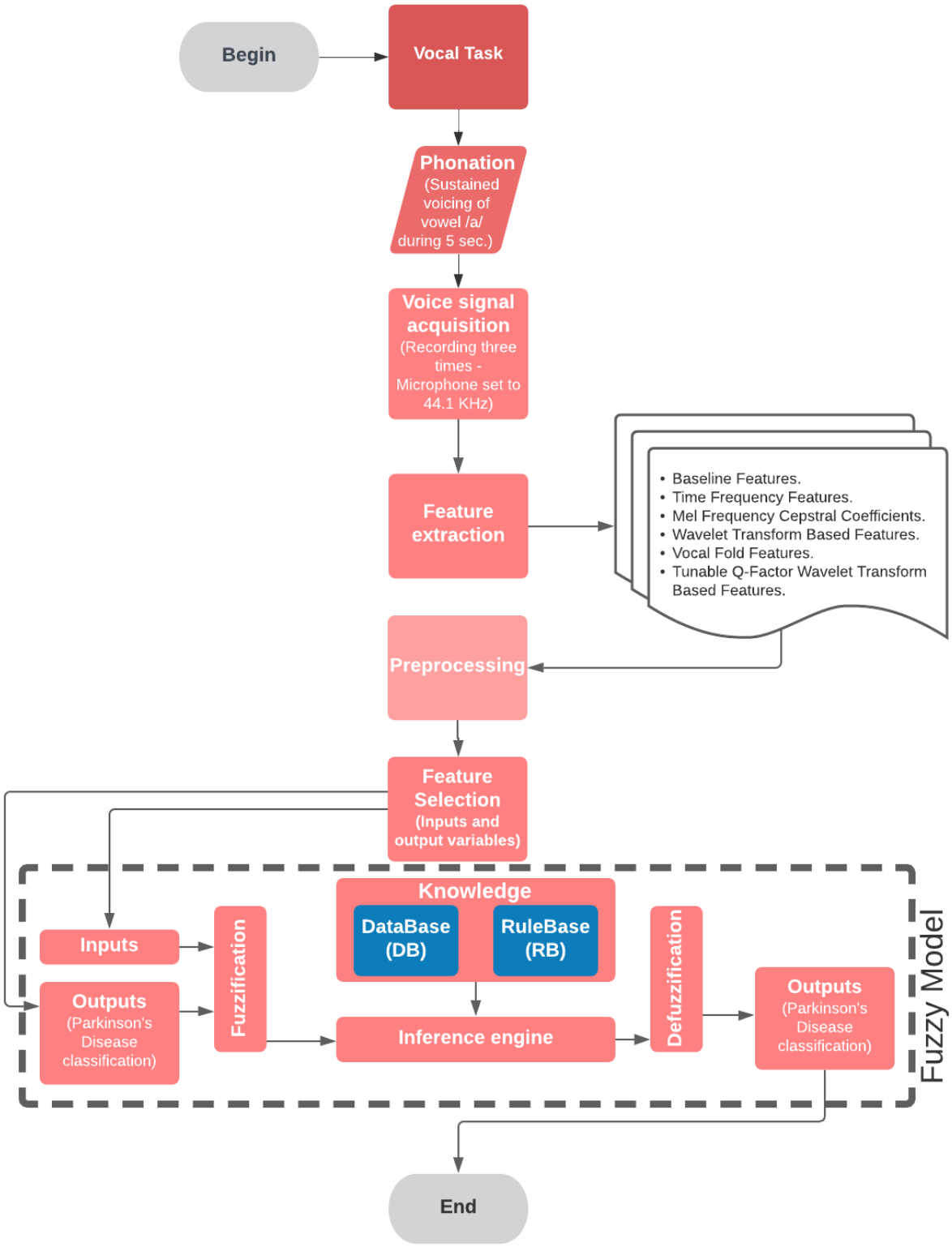

Figure 2.
The proposition of the Fuzzy Model implementation.

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The dataset used in this study was obtained from the UC Irvine Machine Learning Repository [6]. It consists of voice recordings of 188 patients with PD (107 men and 81 women) aged 33 to 87 (65.1±10.9) at the Department of Neurology at Cerrahpaşa Faculty of Medicine, Istanbul University. The control group comprises 64 healthy individuals (23 men and 41 women) aged between 41 and 82 (mean age 61.1 ± 8.9). Each subject phonated the vowel "a" three times, with recordings taken using a microphone set to a 44.1 kHz sampling rate. The dataset features 756 instances with 754 attributes - 753 input variables and one output variable. Importantly, this dataset has no missing values, and all attributes are of integer or real type. This dataset, donated in November 2018, presents a classification challenge. [6]. The dataset contains a rich collection of features, summarized in Table 1. The baseline features of the dataset are visually represented in Figure 3.

Table 1.
Summary of the feature collections utilized in the research (excluding TQWT).

Feature set	Measure	Explanation	# of features
Baseline features	Jitter variants	Variations in jitter are utilized to detect the irregularities present in the vibrating pattern of the vocal cords. This subset of features quantifies the fluctuations in fundamental frequency from one vocal fold cycle to the next.	5
	Shimmer variants	Shimmer variations are also utilized to capture the vibratory pattern of the vocal cords. In this case, this subset of features quantifies the fluctuations in amplitude from one vocal fold cycle to the next.	6
	Fundamental frequency parameters	The frequency of vibration of the vocal folds was examined. This frequency's mean, median, standard deviation, minimum, and maximum values were employed for analysis.	5
	Harmonicity parameters	Because of incomplete closure of the vocal folds, speech pathologies often lead to increased noise components. Parameters like Harmonics to Noise Ratio and Noise to Harmonics Ratio were utilized as features, which help quantify the balance between signal information and noise in the speech.	2
	Recurrence Period Density Entropy (RPDE)	RPDE gives information about the ability of the vocal folds to sustain stable vocal fold oscillations and quantifies the deviations from F_0.	1
	Detrended Fluctuation Analysis (DFA)	DFA quantifies the stochastic self-similarity of the turbulent noise.	1
	Pitch Period Entropy (PPE)	PPE measures the impaired control of fundamental frequency F_0 using a logarithmic scale.	1
Time-frequency features	Intensity Parameters	Intensity is connected to the power of the speech signal, typically measured in decibels (dB). This study employed the mean, minimum, and maximum intensity values as features.	3
	Formant Frequencies	Frequencies enhanced by the vocal tract, known as formants, were utilized as features in this study. The first four formants were explicitly selected for analysis.	4
	Bandwidth	The first four bandwidths were utilized as features within the frequency range spanning the formant frequencies.	4
Mel Frequency Cepstral Coefficients (MFCCs)	MFCCs	MFCCs are used to detect the impacts of Parkinson's disease on the vocal tract, distinct from its effects on the vocal folds.	84

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Wavelet Transform based Features	Wavelet transform (WT) features related to F_0	WT features quantify the deviations in F_0	182
Vocal fold features	Glottis Quotient (GQ)	GQ provides insights into the durations of glottis opening and closing, indicating the regularity in glottis movement.	3
	Glottal to Noise Excitation (GNE)	GNE measures the level of turbulent noise resulting from inadequate closure of the vocal folds within the speech signal.	6
	Vocal Fold Excitation Ratio (VFER)	VFER calculates the quantity of noise generated due to abnormal vocal fold vibration, utilizing nonlinear energy and entropy principles.	7
	Empirical Mode Decomposition (EMD)	EMD decomposes a speech signal into an elementary signal	6

Baseline features																				
PPE	DFA	RPDE	Fundamental frequency pa-rameters				Jitter variance					Shimmer variance							Harmonity parameters	
PPE	DFA	RPDE	3	umPeriodsPulse	meanPeriodPulses	dDevPeriodPuls	locPctJitter	locAbsJitter	rapJitter	ppq5Jitter	ddpJitter	locShimmer	locDbShimmer	apq3Shimmer	apq5Shimmer	apq11Shimmer	ddaShimmer	utoCorrHarmse	ToHarmHarm	ToNoiseHar	class
0.85247	0.71826	0.57227	240	239	0.00806353	0.0000868	0.00218	0.0000176	0.00067	0.00129	0.002	0.05883	0.517	0.03011	0.03496	0.04828	0.09034	0.970805	0.036223	18.995	1
0.76686	0.69481	0.53966	234	233	0.008258256	0.0000731	0.00195	0.0000161	0.00052	0.00112	0.00157	0.05516	0.502	0.0232	0.03675	0.06195	0.06961	0.984322	0.017974	21.497	1
0.85083	0.67604	0.58982	232	231	0.00833959	0.0000604	0.00176	0.0000147	0.00057	0.00111	0.00171	0.09902	0.897	0.05094	0.06497	0.07772	0.15282	0.974846	0.026313	17.651	1
0.41121	0.79672	0.59257	178	177	0.010857733	0.000182739	0.00419	0.0000455	0.00149	0.00268	0.00446	0.05451	0.527	0.02395	0.02857	0.04462	0.07185	0.968343	0.042003	19.865	1
0.3279	0.79782	0.53028	236	235	0.008161574	0.002668863	0.00535	0.0000437	0.00166	0.00227	0.00499	0.0561	0.497	0.02909	0.03327	0.05278	0.08728	0.975754	0.027139	19.557	1
0.5078	0.78744	0.65451	226	221	0.007631204	0.002696381	0.00783	0.0000597	0.00232	0.00312	0.00697	0.07752	0.678	0.03805	0.04767	0.06451	0.11415	0.90672	0.137088	14.676	1
0.76095	0.62145	0.54543	322	321	0.005990989	0.000107266	0.00222	0.0000133	0.00036	0.00094	0.00108	0.03203	0.28	0.0155	0.01971	0.03274	0.0465	0.984564	0.015745	18.67	1
0.83671	0.62079	0.51179	318	317	0.006073855	0.000135739	0.00282	0.0000171	0.00034	0.00088	0.00103	0.063	0.539	0.02949	0.04091	0.06445	0.08848	0.987625	0.012621	20.302	1
0.80826	0.61766	0.50447	318	317	0.006057188	0.0000693	0.00161	0.00000973	0.00027	0.00068	0.00081	0.02783	0.244	0.01376	0.0176	0.02698	0.04129	0.992393	0.00769	22.376	1
0.85302	0.62247	0.54855	493	492	0.003910221	0.0000399	0.00075	0.00000293	0.00009	0.00025	0.00027	0.0567	0.512	0.02692	0.03344	0.0563	0.08077	0.994504	0.005538	23.426	1
0.80657	0.67256	0.61745	488	487	0.003956114	0.0000538	0.00083	0.00000329	0.0001	0.00026	0.00029	0.06639	0.641	0.03747	0.03516	0.05412	0.11241	0.98322	0.017416	19.889	1
0.82653	0.58326	0.44555	498	497	0.003872688	0.0000326	0.00069	0.00000268	0.00007	0.00021	0.00022	0.02531	0.218	0.01283	0.0138	0.02256	0.03849	0.99743	0.00258	27.095	1
0.8726	0.78996	0.78026	492	491	0.003924152	0.0000672	0.0028	0.000011	0.00077	0.00184	0.0023	0.20811	1.814	0.08936	0.14476	0.27669	0.26808	0.797841	0.265575	6.301	1
0.81148	0.76831	0.70809	305	304	0.006316424	0.003245324	0.00341	0.0000216	0.00093	0.00141	0.0028	0.13878	1.326	0.0722	0.0901	0.11271	0.21661	0.93533	0.070261	12.354	1
0.80978	0.77992	0.6918	291	290	0.006624185	0.002756584	0.00457	0.0000303	0.00159	0.00292	0.00477	0.13069	1.222	0.07043	0.09023	0.10685	0.21129	0.953419	0.049389	13.735	1
0.81471	0.61483	0.33216	300	299	0.006433293	0.0000388	0.00085	0.00000545	0.00017	0.00042	0.00051	0.04046	0.354	0.01756	0.02433	0.0469	0.05269	0.997255	0.002758	27.642	1
0.83269	0.62018	0.37051	286	285	0.006754263	0.0000517	0.00111	0.00000752	0.00024	0.00059	0.00072	0.02995	0.266	0.01211	0.01732	0.03501	0.03632	0.995654	0.004375	25.185	1
0.82016	0.63124	0.37031	266	265	0.007256724	0.0000486	0.00086	0.00000628	0.0002	0.00045	0.00059	0.02734	0.241	0.01309	0.01662	0.02548	0.03926	0.996592	0.003428	26.686	1
0.78067	0.66085	0.44583	283	282	0.006824086	0.000138247	0.00177	0.0000121	0.00025	0.00061	0.00075	0.0481	0.422	0.02602	0.02692	0.03984	0.07806	0.991104	0.009076	23.084	1
0.79774	0.71199	0.36714	289	288	0.006693036	0.0000649	0.00122	0.00000819	0.0002	0.00049	0.00061	0.08552	0.741	0.04596	0.05921	0.06201	0.13788	0.99432	0.005729	23.753	1
0.82169	0.62901	0.36176	292	291	0.006623612	0.000028	0.00084	0.00000558	0.00018	0.00041	0.00055	0.02324	0.205	0.01087	0.0125	0.02123	0.03262	0.996298	0.003728	26.489	1
0.43551	0.81029	0.71652	267	266	0.007226883	0.000200238	0.00653	0.0000472	0.00244	0.00389	0.00731	0.22066	1.891	0.09811	0.10565	0.06615	0.29433	0.829794	0.212443	7.254	1
0.7622	0.73507	0.75672	175	165	0.009677449	0.00321833	0.01268	0.000122721	0.00494	0.00499	0.01482	0.13048	1.246	0.0632	0.06968	0.08788	0.18961	0.767873	0.377305	7.194	1
0.38987	0.77921	0.6648	269	268	0.00718394	0.0000955	0.00311	0.0000223	0.00085	0.00182	0.00255	0.067457503	0.606084525	0.034415969	0.04113052	0.055173155	0.103247815	0.686465	0.460579	3.425	1
0.82878	0.67313	0.4662	262	261	0.007371105	0.0000867	0.00212	0.0000156	0.00038	0.00093	0.00115	0.03543	0.315	0.0162	0.01983	0.03772	0.04859	0.9839	0.016531	19.116	1
0.80489	0.62426	0.47446	285	284	0.006776156	0.0000722	0.0015	0.0000101	0.00026	0.00068	0.00078	0.03318	0.293	0.01272	0.02001	0.03957	0.03816	0.992843	0.007236	23.072	1
0.8227	0.62982	0.56243	289	288	0.006642625	0.000078	0.00141	0.00000934	0.00025	0.00062	0.00075	0.04543	0.405	0.01974	0.02897	0.04991	0.05921	0.990845	0.009324	22.266	1
0.8621	0.60863	0.46038	332	331	0.005820732	0.0000613	0.00143	0.00000831	0.00018	0.00049	0.00054	0.04009	0.348	0.02009	0.02365	0.03813	0.06026	0.99341	0.006663	23.641	1
0.83607	0.61289	0.43513	333	332	0.005805192	0.0000591	0.00134	0.00000781	0.00019	0.00051	0.00057	0.05599	0.497	0.0225	0.03188	0.05916	0.0675	0.99437	0.005722	25.301	1
0.84043	0.60437	0.39889	331	330	0.005837888	0.0000559	0.0014	0.00000816	0.0002	0.00053	0.0006	0.03496	0.3	0.01645	0.02051	0.03794	0.04934	0.994327	0.005727	24.249	1
0.79196	0.66429	0.69379	212	211	0.009104241	0.000111466	0.00354	0.0000322	0.00128	0.00228	0.00383	0.1214	1.105	0.05649	0.07947	0.12003	0.16946	0.928883	0.090889	13.831	1
0.3086	0.64823	0.62249	248	247	0.007782401	0.000075	0.00199	0.0000155	0.00066	0.00138	0.00199	0.09149	0.817	0.03894	0.05828	0.10523	0.11682	0.972014	0.029798	17.369	1
0.36894	0.64326	0.59772	237	236	0.00815993	0.0000741	0.00175	0.0000143	0.00051	0.00105	0.00152	0.0944	0.898	0.03973	0.05654	0.10078	0.11919	0.973316	0.028338	17.581	1
0.82127	0.66846	0.26212	375	374	0.005138503	0.0000436	0.00086	0.0000044	0.00009	0.00025	0.00028	0.03564	0.316	0.02002	0.02042	0.02589	0.06005	0.994753	0.00531	24.058	0

Figure 3.
Image of the baseline features dataset.

3.2. Initial System Design (Steps 4-5)

Following domain analysis, the next phase involved designing the initial system architecture. This phase includes defining the features to be extracted from the voice data, as well as the preprocessing steps:

Feature Selection: Acoustic features such as jitter, shimmer, harmonic-to-noise ratio (HNR), Baseline, and Mel Frequency Cepstral Coefficients (MFCCs) were selected based on their relevance in identifying voice impairments linked to PD.

3.2.1 Data Preprocessing:

Data Cleaning: Noisy and irrelevant data were filtered to improve model performance.

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Normalization: Feature values were normalized to a standard scale to prevent biases during model training.

Data Splitting: There were two types of data-splitting methods. Random sampling: The dataset was split into training and testing sets in different ratios (%): 50-50, 70-30, 80-20, 100-0, ensuring a robust evaluation of the model's performance. The other method used was the Cross-Validation with k = 10 folds.

3.3. Iterative Design and Development (Steps 6-9)

This phase focuses on the iterative design and construction of the decision support system, primarily focusing on the fuzzy logic model.

3.3.1. Knowledge Database Creation (Steps 7–8):

A knowledge database was built using voice features systematically analyzed for their relevance in distinguishing between PD and healthy individuals.

Pivot Tables: Pivot tables were used to analyze the relationships between the acoustic features and the binary classification outcome (PD vs. healthy). This analysis was the foundation for the feature selection process, identifying which features contributed the most to the classification.

3.3.2. Rule Base Creation (Step 9):

A knowledge rule base was constructed based on the insights gained from the pivot table analysis. Fuzzy if-then rules were generated to model the relationships between voice features and the likelihood of PD. The knowledge rule base forms the core of the fuzzy inference system, allowing the model to make transparent decisions based on these rules.

3.4. Implementation and Evaluation of the Fuzzy Logic Models (Steps 10-11)

The next phase involves the implementation and evaluation of the Mamdani-type fuzzy logic model:

3.4.1. Mamdani-Type Fuzzy System

The fuzzification process converted numerical values of the voice features into linguistic variables such as "Very low," "Low," "Moderately low," "Medium-low," "Medium-high," "Moderately high," "High," and "Very high." Triangular and trapezoidal membership functions defined the boundaries of these linguistic variables.

The inference engine applied the fuzzy if-then rules to combine these linguistic variables and generate a fuzzy output representing the likelihood of PD.

Finally, the defuzzification process converted the fuzzy output into a crisp classification (either PD or healthy).

3.4.2. Evaluation

In this stage, the performance and reliability of the developed fuzzy model are rigorously assessed employing several evaluation metrics, which include:

Classification Accuracy
Sensitivity
Specificity
Function Measure
Area Under the Curve (AUC)
Kappa Statistics

A detailed exploration and explanation of these metrics, including their respective mathematical formulations, are delineated in [31]. (Please refer to Appendix A for a thorough exposition of the experiments conducted.)

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3.4.2.1. Calculating Classification Accuracy

Classification accuracy is a pivotal metric that quantitatively measures the model's ability to classify instances correctly. It is computed as follows:

During this phase, the efficacy of the fuzzy model was assessed using the subsequent metrics: classification accuracy, sensitivity, specificity, Function Measure, Area under the curve (AUC), and Kappa statistics. These evaluation metrics are comprehensively described in [31] with their respective formulae (All the experiments are available in Appendix A). The classification accuracy was determined by computing the ratio of the sum of true positives (TP) and true negatives (TN) achieved through the classification algorithms to the total count of occurrences, as defined by the equation (1).

$$ACC = \frac{TP + TN}{TP + FP + FN + TN} \quad (1)$$

Where:

TP represents True Positives
TN symbolizes True Negatives
FP denotes False Positives
FN indicates False Negatives

The accuracy value (ACC) represents the ratio of the correctly classified instances (positive and negative) to the total cases in the dataset, thereby providing a concise yet comprehensive measure of the model's classification precision. Consequently, this metric provides an overall snapshot of how effectively the fuzzy model echoes the observed classification outcomes, offering a transparent insight into its general predictive capability.

4. Results

We validated the best fuzzy model, juxtaposing it with alternative models that similarly aimed to predict the output variable through the interaction of inputs.

The performance of the proposed Mamdani-type fuzzy logic model was evaluated using two different methods: 10-fold cross-validation and random sampling (different ratios). The accuracy, measured using R^2 coefficients, was computed for various feature sets, including VFF, Wavelet Transform (WT), TQWT, MFCCs, Intensities, Baseline, and the combination of all features. The results highlight the robustness of the model across different datasets and feature sets.

4.1. Performance Evaluation Using Cross-Validation (10-Folds)

The cross-validation results in Table 2 present the R^2 accuracy coefficients across different datasets and feature sets. As seen, the model achieved consistently high performance across most datasets, with a maximum R^2 value of 0.975 for several feature sets, including VFF, WT, TQWT, and MFCCs. The performance remained stable for the training data, with an R^2 value of 1.0 across most feature sets. In contrast, the test set performance showed some variability, particularly with intensities, with a lower test R^2 value of 0.638.

Table 2.
Mean of Accuracy percentage (R^2 coefficients) for datasets and number of features (Cross-validation 10-folds).

Datasets/Features	VFF	WT	TQWT	MFCC	Intensities	BWF	Baseline	All Features
All dataset	0.975	0.975	0.975	0.975	0.640	0.975	0.971	0.975
Training	1.000	1.000	1.000	1.000	0.634	0.999	0.994	1.000
Test	0.744	0.744	0.747	0.744	0.638	0.750	0.762	0.744

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These results demonstrate the model's ability to generalize across different feature sets, with a slight drop in performance when using intensities as the primary feature.

4.2. Performance Evaluation Using Random Sampling (80-20%)

Table 3 shows the accuracy results obtained using random sampling with an 80-20% train-test split. The model achieved strong performance on the training sets, with R^2 values 1.0 for most feature sets. However, the test set performance varied slightly, with the highest R^2 value of 0.861 achieved for VFF and Baseline features. The intensities dataset again showed the lowest performance on the test set, with an R^2 value of 0.748.

Table 3.
Accuracy percentage (R^2 coefficients) for datasets and number of features (Random sampling 80-20%).

Datasets/Features	VFF	WT	TQWT	MFCC	Intensities	BWF	Baseline	All Features
All dataset	0.972	0.968	0.971	0.971	0.787	0.968	0.972	0.968
Training	1.000	1.000	1.000	1.000	0.797	1.000	1.000	1.000
Test	0.861	0.841	0.854	0.854	0.748	0.841	0.861	0.841

4.3. Analysis and Comparisons

The results indicate that the proposed fuzzy logic model performs consistently well across various feature sets and evaluation methods. Notably:

- The VFF, WT, TQWT, and MFCC feature sets showed the highest performance in cross-validation and random sampling methods, with test R^2 values ranging between 0.744 and 0.861.
- The intensities feature set consistently underperformed compared to the other sets, with R^2 values of 0.640 in cross-validation and 0.748 in random sampling. This suggests that intensities alone may not provide sufficient discriminatory power for PD classification.
- The baseline and all-features set performed well, with the test set R^2 values close to those of VFF, WT, and TQWT, indicating that these feature combinations can offer robust classification performance.

The cross-validation results show stable model performance across different training and test splits. In contrast, the random sampling results confirm that the model can generalize well to unseen data, mainly using the Baseline, VFF, TQWT, and MFCC feature sets.

Table 4 reveals the number of clusters utilized for each subset or group of features, having derived the values from training with 100% of the dataset. The chief aim was to discern the number of clusters necessary to achieve 100% classification accuracy with a single iteration. Once this value was identified, training could proceed with other percentages. As previously mentioned, the minimum value for training with the complete dataset was two. If the cluster number is five, then prior numbers did not accomplish 100% classification accuracy. Similarly, if the value exceeds ten (as in Intensity-Based), it could not attain 100% classification accuracy. Nonetheless, training occurred with the optimal number calculated using pivot tables (Section 5). Table 4 displays the number of clusters for each input variable for optimal performance in individual datasets.

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Table 4.
Clusters numbers for every input variable for the best performance in individual datasets.

Feature Group	Number of Clusters
WT—182	5
Baseline—21	8
VFF—22	4
TQWT—432	2
All features—753	2
MFFCs—84	2
Bandwidth + Formant—8	10
Intensity-Based—3	27

Note: WT: Wavelet Transformation. VFF: Vocal Fold Features. TQWT: Tuneable Q-Factor wavelet transform. MFFCs: Mel Frequency Cepstral Coefficients.

Table 5 and Figure 4 present the performance outcomes of the models for the PD dataset and its corresponding sub-datasets. Table 4 showcases experiment results obtained with individual feature subsets, delineating performance metrics (specificity, sensitivity, precision, recall, F-measure, and Area Under Curve) for all datasets. Figure 4 illustrates the confusion matrices for training (80%) and validation (20%) datasets for the baseline feature group, consisting of 21 features. Class 0 represents healthy individuals, while Class 1 denotes Parkinson's Disease patients.

Table 5.
Experiment results were obtained with individual feature subsets.

Feature Groups—Feature Numbers	Sensitivity	Specificity	Precision	Recall	F-Measure	Area under Curve
	Training: 50–50% Testing					
WT—182	0.8554	1.0000	1.0000	0.8554	0.9392	0.8099
Baseline—21	0.8938	1.0000	1.0000	0.8938	0.9439	0.8255
VFF—22	0.8854	1.0000	1.0000	0.8854	0.9392	0.8099
TQWT—432	0.8854	1.0000	1.0000	0.8854	0.9392	0.8099
All features—753	0.8854	1.0000	1.0000	0.8854	0.9392	0.8099
MFFCs—84	0.8854	1.0000	1.0000	0.8854	0.9392	0.8099
Bandwidth + Formant—8	0.8812	1.0000	1.0000	0.8812	0.9369	0.8021
Intensity-Based—3	0.8489	0.5400	0.8369	0.8489	0.8429	0.6997
	Training 70–30% Testing					
WT—182	0.9400	1.0000	1.0000	0.9400	0.9691	0.9063
Baseline—21	0.9276	1.0000	1.0000	0.9276	0.9625	0.8854
VFF—22	0.9353	1.0000	1.0000	0.9353	0.9666	0.8984
TQWT—432	0.9322	1.0000	1.0000	0.9322	0.9649	0.8932
All features—753	0.9322	1.0000	1.0000	0.9322	0.9649	0.8932
MFFCs—84	0.9353	1.0000	1.0000	0.9353	0.9666	0.8984
Bandwidth + Formant—8	0.9338	1.0000	1.0000	0.9338	0.9658	0.8958
Intensity-Based—3	0.8270	0.5839	0.8901	0.8270	0.8574	0.6716
	Training 80–20% Testing					
WT—182	0.9641	1.0000	1.0000	0.9641	0.9817	0.9453
Baseline—21	0.9696	1.0000	1.0000	0.9696	0.9800	0.9401
VFF—22	0.9641	1.0000	1.0000	0.9641	0.9817	0.9453
TQWT—432	0.9625	1.0000	1.0000	0.9625	0.9809	0.9427
All features—753	0.9608	1.0000	1.0000	0.9608	0.9800	0.9401
MFFCs—84	0.9353	1.0000	1.0000	0.9353	0.9666	0.8984
Bandwidth + Formant—8	0.9592	1.0000	1.0000	0.9592	0.9792	0.9375
Intensity-Based—3	0.8480	0.5876	0.8706	0.8480	0.8591	0.7061
	Training 100–0% Testing					
WT—182	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Baseline—21	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VFF—22	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
TQWT—432	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

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All features—753	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MFFCs—84	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Bandwidth + Formant—8	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Intensity-Based—3	0.8270	0.5839	0.8901	0.8270	0.8574	0.6716

Note: WT: Wavelet Transformation. VFF: Vocal Fold Features. TQWT: Tuneable Q-Factor wavelet transform. MFFCs: Mel Frequency Cepstral Coefficients. Bold values indicate the best performance.

Table 6.
Matrix confusion of the datasets (training (a) and test (b)) for the baseline feature group, with 21 features. Class 0 means healthy people, and Class 1 means Parkinson's disease patients.

(a)		
	Class 0	**Class 1**
Class 0	165	0
Class 1	0	440
(b)		
	Class 0	Class 1
Class 0	4	23
Class 1	0	124

In Appendix A, all the fuzzy inference models developed in the experiments are listed. The model with the optimal configuration of the best fuzzy inference system used to predict Parkinson's disease, including inputs, output, and samples from the knowledge rule base is located in the folder path folder/80-20/21 baseline trained Acc_0.972 1 0.861_#Vars_21__NaVars_more than 20 variables_Parkinson_Outputs.fis.

5. Discussion

The performance of the proposed Mamdani-type fuzzy logic model for classifying Parkinson's Disease (PD) based on voice signals was evaluated using two methods: 10-fold cross-validation and random sampling (80-20%). The results demonstrate the model's effectiveness in achieving high accuracy across multiple feature sets but also reveal specific insights regarding the contribution of different acoustic features.

5.1. Key Findings

The fuzzy logic model consistently achieved high R^2 accuracy coefficients for several feature sets, particularly VFF, WT, TQWT, and MFCC. In both cross-validation and random sampling, these feature sets resulted in test set R^2 values ranging from 0.744 to 0.861, showing the robustness of these features in distinguishing between PD patients and healthy controls.

The VFF and Baseline features sets showed the highest performance in both methods, with a test R^2 of 0.861 in random sampling and 0.744 - 0.762 in cross-validation, respectively. This suggests that vocal fold frequency characteristics are highly predictive of PD, likely due to their sensitivity to early vocal changes caused by the disease.

Similarly, WT and TQWT feature sets also performed strongly, showing that these time-frequency transformation techniques can capture the subtle variations in vocal signals associated with PD.

In contrast, the intensities feature set performed poorly compared to the others, with test R^2 values of 0.638 in cross-validation and 0.748 in random sampling. This indicates that intensity-based features alone are insufficient to classify PD accurately, likely because changes in vocal intensity may be less consistent or pronounced in the early stages of the disease.

5.2. Comparative Analysis of Evaluation Methods

When comparing the two evaluation methods (cross-validation and random sampling), the random sampling method showed slightly better performance on the test set, particularly for the VFF and baseline feature sets. The highest test R^2 value obtained was 0.861 for VFF and baseline under random

sampling. At the same time, the cross-validation method resulted in slightly lower values, with a maximum test R^2 of 0.762 for the baseline feature set.

This difference in performance could be attributed to the inherent variability in cross-validation, where the model is tested on different subsets of the data. In contrast, random sampling provides a fixed training and test set, which may lead to more stable results in some instances. However, both methods confirm the robustness of the fuzzy logic model across different feature sets, mainly when using frequency-domain features like VFF and TQWT.

5.3. Implications for Clinical Applications

The results of this study have several implications for the potential clinical application of the fuzzy logic model in early PD detection:

- Vocal fold frequency characteristics (VFF) and time-frequency transformations (WT, TQWT) effectively detect the subtle vocal impairments associated with PD, making them valuable features for developing non-invasive diagnostic tools.
- The high accuracy and stability of the model across multiple evaluation methods suggest that the fuzzy logic system could be implemented in clinical decision support systems to aid in the early detection of PD. The interpretability of the fuzzy logic model also makes it a suitable choice for clinical environments where transparency in decision-making is critical.
- While the intensity-based features did not perform as well, their inclusion in combination with more predictive features (e.g., VFF, TQWT) may still provide complementary information, particularly in later stages of the disease when vocal intensity might change more dramatically.

To validate our results, we juxtaposed them with various studies from existing literature, with a selection criterion based on their recentness and demonstrated effectiveness in classification tasks using similar Parkinson's Disease datasets.

Reference [32] devised a method intertwining minimum average maximum (MAMa) tree and singular value decomposition (SVD) for future extraction, comprising pre-processing, feature extraction, feature selection, and classification stages. Two cases were employed in the application, each utilizing a different combination of these stages, and 1-NN and k-NN classifiers were identified as providing optimal classification accuracies for Case 1 and Case 2, respectively. Remarkably, our results exhibited higher classification accuracy with fewer features than this study.

In another study, Reference [15] scrutinized the influence of neuron numbers and activation functions in a Deep Neural Network (DNN) model, optimizing its performance via a growing and pruning methodology. Although a superior performance on the test dataset was achieved, our algorithms consistently achieved a 100% classification accuracy rate on the training dataset. Furthermore, our results for 80–20% of training datasets surpassed those acquired by the author, even with a reduced feature set.

In a different approach, Reference [16] employed six supervised machine learning algorithms, obtaining a maximum classification accuracy of 76% using linear discriminant analysis (LDA) across all datasets. Our results showcased competitive with or superior performance compared to these findings.

Moreover, Reference [33] explored the future extraction process using Wrappers feature subset selection and four classification techniques. Despite achieving notable outcomes, our performance metrics results prevailed in comparison.

Reference [34] applied a gender-based dataset division using a Simple Logistic hybrid system. Although reasonably accurate results for both genders were obtained, our results demonstrated superior accuracy and AUC values.

While Reference [6] adopted the tuneable Q-factor wavelet transform (TQWT) and several machine learning classifiers for PD classification, our proposed method yielded higher metrics without relying on this classifier.

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Following the processes and stages for designing fuzzy systems as laid out by Hernández-Julio, et al. [20] and Hernández-Julio, et al. [19], this approach was characterized by several distinctions and similarities in comparison to previously cited studies and established frameworks:

- Identification of Variables: Both our approach and others identified input and output variables for Parkinson's disease classification using similar datasets.
- Formulating Membership Functions: Unlike other methodologies that use various algorithms to define membership functions, the framework proposed by Hernández-Julio, et al. [20] allows for a manual choice of the number of functions via clustering techniques, thereby avoiding reliance on randomness or evolutionary algorithms.
- Rule Base Generation: Using pivot tables does not require calculations, random factors, or manual parameters to create the fuzzy rule base, which distinguishes our method from those that involve random weights and objective functions. The simplicity and directness of this technique stand out by focusing on minimizing redundant information.

The parameters applied within the framework, such as the choice of input and output variables, selection of clustering algorithms, and data partition method, are straightforward and do not necessitate adjustments for random values, weights, or other variables (Figure 5). Additionally, internal adjustments were confined to those used for clustering methods. The minimalistic approach toward computational demand and our algorithms' accurate and efficient processing contribute to a straightforward comprehension of the rules.

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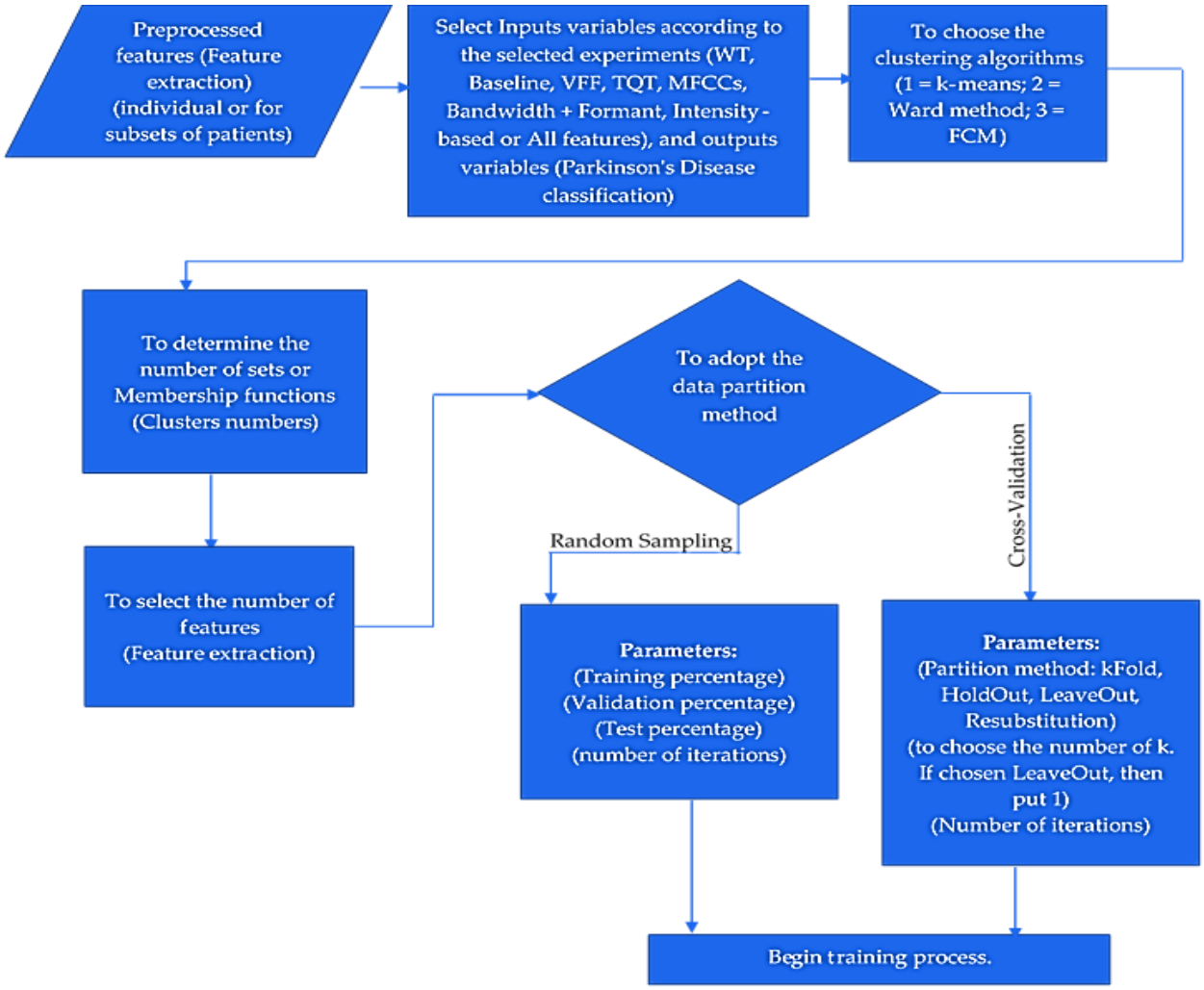

Figure 5.
Required parameters of the proposed framework.

The efficacy of our framework has been demonstrated across varied domains, including Medicine [18, 20]. Bioengineering [34]. Aquaculture [35] and Colombian Business Finances [36] indicating its versatile applicability to diverse problems contingent on data availability.

According to the results, the FIS with the best performance revealed optimal performance using the baseline dataset with fewer features (applying random sampling and cross-validation) and allocating 80% for training and the remaining 20% for validation. With a classification accuracy of 97.2%, sensitivity and recall of 0.9696, specificity and precision of 1.0, F-Measure of 0.98, and an AUC of 0.9401 for complete datasets, these results can potentially be harnessed in telediagnosis and telemonitoring systems for preliminary disease detection, thereby mitigating the necessity for frequent clinic visits and alleviating clinician workloads, irrespective of pandemic circumstances. The Fuzzy Model, applicable individually or to patient subsets (Appendix B), is thus presented as a viable tool for Parkinson's disease classification.

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5.4. Limitations and Future Directions

Despite the promising results, several limitations of this study should be addressed in future research:

- The dataset used in this study is relatively small and consists of voice recordings from a limited population. To ensure the model's generalizability, future work should involve more extensive and diverse datasets, including data from different age groups, genders, and stages of PD progression.
- Although the fuzzy logic model showed high accuracy, adding more advanced feature selection techniques could further optimize the model's performance. For instance, combining pivot table analysis with machine learning-based feature selection could help refine the most important features for classification.
- The current study focuses on voice signals as the primary data source. Future research could explore combining voice data with other non-invasive biomarkers, such as gait analysis or handwriting patterns, to develop a more comprehensive early detection system for PD.

6. Conclusions

In conclusion, the selected Mamdani-type fuzzy logic model demonstrated strong classification performance for PD detection using voice signals, with VFF, Baseline, and TQWT feature sets showing the highest accuracy. The results underscore the potential of non-invasive voice-based diagnostic tools for early PD detection. Future work should focus on validating the model with larger datasets and exploring the integration of multiple data sources to improve diagnostic accuracy further.

Institutional Review Board Statement:

The study was conducted according to the principles outlined in the Declaration of Helsinki and was approved by the Clinical Research Ethics Committee of Bahcesehir University.

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Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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Appendix A

https://drive.google.com/file/d/15dgUc58aOSaPRSs-dHZw9Qn_natgU-E8/view?usp=sharing (accessed on 19 March 2024).

Appendix B

https://drive.google.com/file/d/1oTTVn5a5lClmh5oKm6ClI5TuVIsG73cf/view?usp=sharing (accessed on 19 March 2024).

Declaration of Generative AI and AI-assisted technologies in the writing process

While preparing this article, the authors used ChatGPT premium to improve their readability and language because the authors are not native English speakers. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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