Distinguishing Diagnostic Paradigms for Parkinson's Disease: An Advanced Exploration

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ABSTRACT
Parkinson's disease (PD) is a neurological disease affecting the elderly. The gradual degradation of dopamine-producing neurons is its hallmark. The lack of manual diagnosis protocols in poor nations leads to physician disagreements and insufficient healthcare resource allocation. As a result, there is an increased need for automated, artificial intelligence-powered diagnostic solutions. Electroencephalography (EEG) data is intriguing for this study of Parkinson's disease (PD) and its mysterious symptoms. EEG anomalies and interferences impair diagnostic interpretation. Noise disrupts the brain's rhythm, requiring precise signal processing to extract authentic material. However, despite the noteworthy exhibition of the signal, definitive biomarkers continue to be challenging to identify, thus requiring the integration of artificial intelligence to harmonize current methodologies and innovative strategies. In the present study, a total of 168 individuals diagnosed with Parkinson's disease (PD) and 39 individuals classified as Healthy Controls (HC) taken from two different databases were included. The combination of EEG signals, and phase dynamics processing methodology, guided by the unique distinguishing properties of a Convolutional Neural Network, demonstrated a remarkable accuracy of 100 % in identifying individuals with Parkinson's disease, surpassing any other method in terms of precision and specificity. The experiment's robustness was confirmed by repeating the process 100 times achieving 99.8 +/- 0.2% accuracy. Additionally, the methods can accurately localize anatomical structures despite varied sampling resources and data durations. This study's discovery of convergence may improve Parkinson's disease diagnosis and patient well-being.

1. Introduction

Parkinson's disease (PD) is characterized by substantia nigra dopamine neuron degeneration [1]. Dopamine is a crucial catecholamine and phenethylamine neurotransmitter. It helps the brain and substantia nigra communicate, improving motor coordination. Parkinson's disease symptoms are caused by a dopamine deficit resulting from the death of 60–80% of brain dopamine-producing cells [2]. This resource shortage impairs motor function regulation, causing motor control symptoms [3]. PD, a motor system disorder, causes tremors, rigidity, balance issues, and bradykinesia [4]. ALS nonmotor symptoms include cognitive impairment, depression, restless legs, heat sensitivity, and gastrointestinal issues. PD has no cure, but many therapies have been developed to reduce both motor and nonmotor symptoms. In [5], they investigated motor control network targeting with noninvasive pharmacological and invasive surgical approaches. Over 90% of PD patients have dysphonia, according to recent studies. This distinguishes them from non-PDers. Nearly 10 million people worldwide have Parkinson's disease (PD), the second most common neurological ailment after Alzheimer's [6]. This illness becomes more common after age 65, with men being more susceptible than women. Interestingly, prodromal symptoms like olfactory impairment, constipation, and sleep disruptions precede motor symptoms by several years. Early treatment is essential to slow illness development [7].

PD and other movement disorders have two phases: the preclinical phase, which includes undiagnosed neurodegeneration, and the prodromal phase, which includes symptoms that do not meet diagnostic criteria [8]. Thus, rapid and correct diagnosis is more important than ever, regardless of stage. Few studies have used EEG data to detect PD [8–10]. EEG recordings can be ruined by body movement, power grid interference, eye blinks, and heartbeats. These issues are the main reason neurodegenerative disorders are not recognized early. To identify neurological disorders using EEG signals, noise must be removed, characteristics extracted, and categories created. Raw EEG data contains artifacts and noise. Thus, EEG data noise must be removed first. After signal separation, noise

was removed using a time, frequency, or time-frequency filter [11]. Al Fahoum et al. extracted important characteristics from filtered data using algorithms [11]. The resulting attributes are loaded into a neuro-disorder detection and classification model. Remember that there are no definite indicators for early Parkinson's disease (PD) diagnosis. This shows the growing importance of integrating AI into diagnostic methods [9]. This work aims to create a computer-assisted diagnostic system that can identify Parkinson's disease patients using EEG data. Previous research has improved noninvasive EEG diagnosis of Parkinson's disease. This diagnostic approach has limitations and is not yet perfect [12].

This work presents new methods for early Parkinson's disease diagnosis to overcome this restriction. This study seeks to enhance Parkinson's disease diagnosis by identifying substantial phase dynamics differences between patients and controls. Feature selection, hyperparameter tweaking, dataset balancing, and dimension reduction help achieve this goal. However, our proposed approach reduces several processing steps by using pertained CNN to connect missing feature links and evolve the solution naturally. This study compares the proposed technique to other newly revealed ways to improve RPS analysis for Parkinson's disease diagnosis. Parkinson's disease management requires quick diagnosis. Using neurology, RPS, and customized deep learning, this research article proposes a new Parkinson's disease detection system using EEG signals. This study uses rigorous feature selection, hyperparameter tuning, and dimensionality reduction methods to investigate PD diagnosis challenges.

2. Literature Review

To better understand this groundbreaking effort, a thorough review of Parkinson's disease diagnosis studies will be conducted. These study findings illuminated various diagnostic issues. Little et al. [13] used an algorithmic tapestry to measure dysphonia and speech analytic approaches to distinguish Parkinson's disease from other conditions. This may lead to a deeper understanding. Diagnostic accuracy was 91.4%, which was good. Recurrence and fractal scaling were used in this study's unique strategy. Canturk et al. [14] examined feature selection. The researchers tested a six-class taxonomy using leave-one-subject-out cross-validation (LOSO CV) and fold CV. The study found that leave-one-subject-out cross-validation (LOSO CV) had a 57.5% accuracy rate and fold CV 68.94%. The research by Almeida et al. [15] and Das et al. [16] shows that magnetic resonance imaging diagnostics have improved. Initial classifiers used phonetic word information. The second method used the unified PD rating scale, partial least squares, and self-organizing maps to diagnose Parkinson's disease (PD). Yuvaraj et al. (2019) examined how electroencephalogram (EEG) data could reveal how Parkinson's disease (PD) patients feel [17]. Spectral decomposition with KNN and SVM classifiers revealed Parkinson's disease patients' diverse emotions. Modern spectrum analysis methods can extract important properties from electroencephalography data in a comparable area. As a result, diagnostic classifiers are expanding [18, 19]. In another study, Sivaranjini et al. examined MR image diagnostics using AlexNet [20]. The results showed 88.9% accuracy, suggesting good precision.

There are now several existing approaches available for the analysis of resting EEG data in order to classify Parkinson's disease (PD). The methodologies employed in previous studies encompass spectrum and complexity analysis [21], the utilization of energy and entropy features in conjunction with a decision tree classifier [22], and the examination of time-frequency characteristics of components derived through blind source separation [23-24]. The authors of the study conducted in [25] employed a flexible analytic wavelet transform (FAWT) to develop a novel algorithm for the automated diagnosis of Parkinson's disease utilizing EEG signals. A new survey is published in reference [26], which examines 61 research articles that focus on the classification of Parkinson's disease (PD). Kwak et al. (year) proposed the development of a one-dimensional convolutional neural network (1D-CNN) for the purpose of classifying characteristics, as opposed to utilizing raw data [27]. The conversion of EEG signals into multispectral pictures has been demonstrated as a viable approach for further classification purposes [28]. This premise is grounded on the notion that the spatial

arrangement of the channels could potentially contribute to the process of categorization. In a previous investigation, a technique known as the "feature-fusion multispectral image method" (FMIM) was proposed for the examination of EEG data obtained from several channels. This method was observed to outperform conventional multispectral image methods, as indicated by prior research [29]. In summary, the data presented in this collection reveals a consistent pattern characterized by a continuous effort to attain precision in the process of diagnosis. Despite the commendable nature of these endeavors, it is evident that the challenge of achieving adequate outcomes in automating the early identification of Parkinson's disease persists. Nevertheless, the existing clinical diagnostic methods lack a systematic approach and do not offer a promising solution for the early detection of Parkinson's disease (PD). Clinical diagnoses are sometimes erroneous due to the frequency of other illnesses that resemble Parkinson's disease (PD). Dementia with Lewy bodies, MSA, PSP, Corticobasal Syndrome, ERT, and NPH are examples [30]. A systematic diagnostic approach that integrates clinical characteristics could slow Parkinson's disease progression. There are no conclusive treatments, yet many therapies exist. Carbidopalevodopa, dopamine agonists, MAO B inhibitors, and Catechol O-methyltransferase (COMT) inhibitors are all medicines used to help people with Parkinson's disease (PD) who have tremors, trouble sleeping, and other symptoms [31]. This study addresses the above concerns to enhance Parkinson's disease diagnosis.

3. Materials and Methods

This article talks about a framework that uses deep learning classification algorithms and frequency-based reconstructed phase space (RPS) to look at signals that aren't staying in the same place. The methodology entails preparing electroencephalogram (EEG) data from different categories, namely normal and Parkinson's, for use inside the system. To reconstruct the outputs of discrete sine transform channels inside a two-dimensional space, the RPS technique is used. The resultant RPS plots are aggregated to create a composite image encompassing all RPSs. The aforementioned photos are subsequently communicated to a deep-learning network to produce categorization outcomes, as depicted in Figure 1.

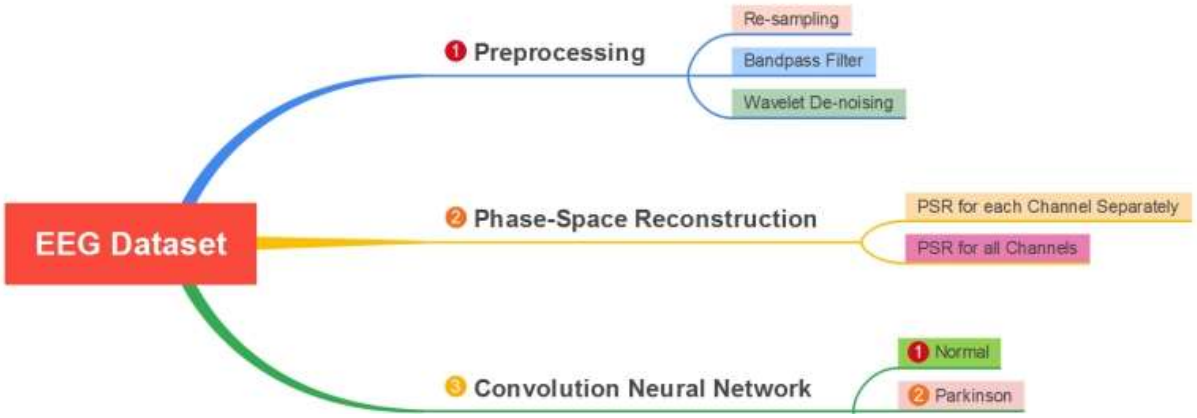

Figure 1. Block diagram of the proposed approach

Data Pr-processing

The current investigation collected EEG data from healthy and schizophrenia-symptomatic teens. The data came from M.V. Lomonosov's Laboratory for Neurophysiology and Neuro-Computer Interfaces. The database comprises 39 typical EEGs. Individual database entries comprise EEG recordings. Every text file has a unique format with one column for 16-channel EEG samples and electrode placements. Each column's millivolt figures reflect the EEG signal's amplitude at sample locations. The first and other samples are 7680. A minute of 128 Hz EEG recording equals 7680 samples [32]. PREDiCT was used to examine Parkinson's disease. The data was collected while patients were at rest. EEG data were taken utilizing 64 channels with unique electrode placements. 30,000 samples from each channel were chosen for a one-minute 500 Hz recording [33]. EEG readings from the three categories were

resampled to 128 Hz and lasted 60 seconds. Table 1 displays the quantity of EEG data points for three study-specific categories.

Table 1. Data set Details

Class	Number of Data
Normal	***39***
Parkinson	***168***
Total of Data	***207***

Because the two classes provided different channel numbers, only the 12 common channels were used. With MATLAB® 2022b, EEG data from these channels was processed. Raw data is preprocessed using an optimized REMEZ band-pass FIR digital filter between 0.5 and 45 Hz. This filter aims to reduce electrical interference from 50/60 Hz line noise and high-frequency noise [34]. When denoising, the wavelet transform method manipulates filter data. The method addresses a variety of muscle and electrode noise types [35]. The multiresolution wavelet transforms decreased baseline drift and noise [36]. This study used Daubechies wavelet (db2) to partition data into six levels. To decrease signal noise, discrete inverse wavelet was applied to the remaining components. Additional preprocessing steps include amplitude normalization. It's optional; however, it helps visualize data comparisons between patients and datasets [36]. Figure 2 shows electroglottography (EGG) samples before and after preprocessing.

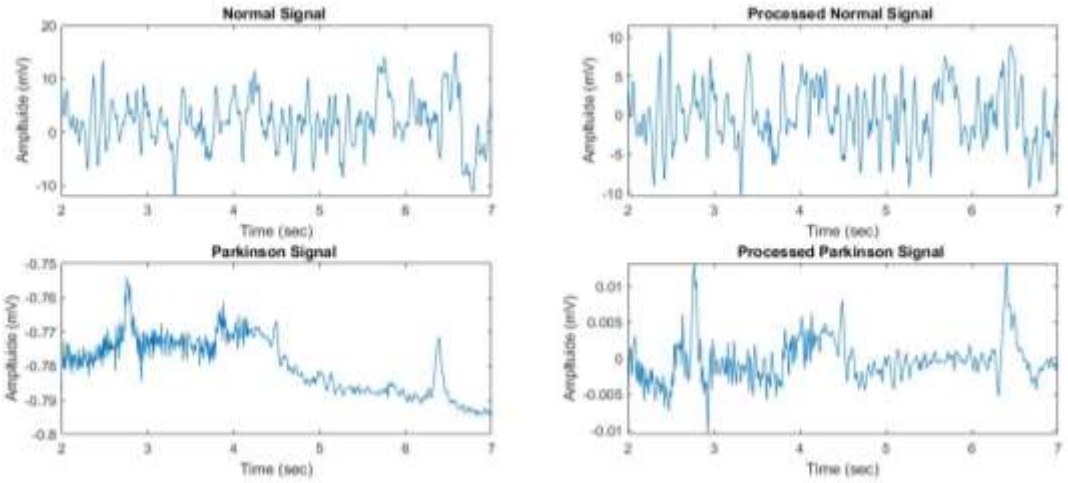

Figure 2. Five seconds of the raw and processed EEG signals representing samples of the normal, and PD signals

Phase-Space Reconstruction

The study then looks at how phase space analysis can be used to reconstruct complex odd-frequency systems. It focuses on how complex biosignals like electrocardiograms (ECG) and electroencephalograms (EEG) are and how they change over time. The phase space concept assumes that the attractor accurately depicts the EEG's phase space dynamics. The reconstruction of phase space entails determining both the embedded size and the delay time, which are critical to understanding the dynamics of various systems. The RPS's details are examined in [36-37]. The reconstruction phase space methodology starts with unprocessed data and generates vectors iteratively, including time delays. The choice of lag time influences the attractor distribution throughout the reconstructed phase space. The initial minimum of the auto mutual information function (AMIF) can be used to find the best time delay for putting a signal into the phase space reconstruction of a nonlinear periodic time series [38]. We used MATLAB® software with a maximum time latency of 10 and embedded dimensions of 3 to compute the results as shown in figures 3, 4, and 5 respectively.

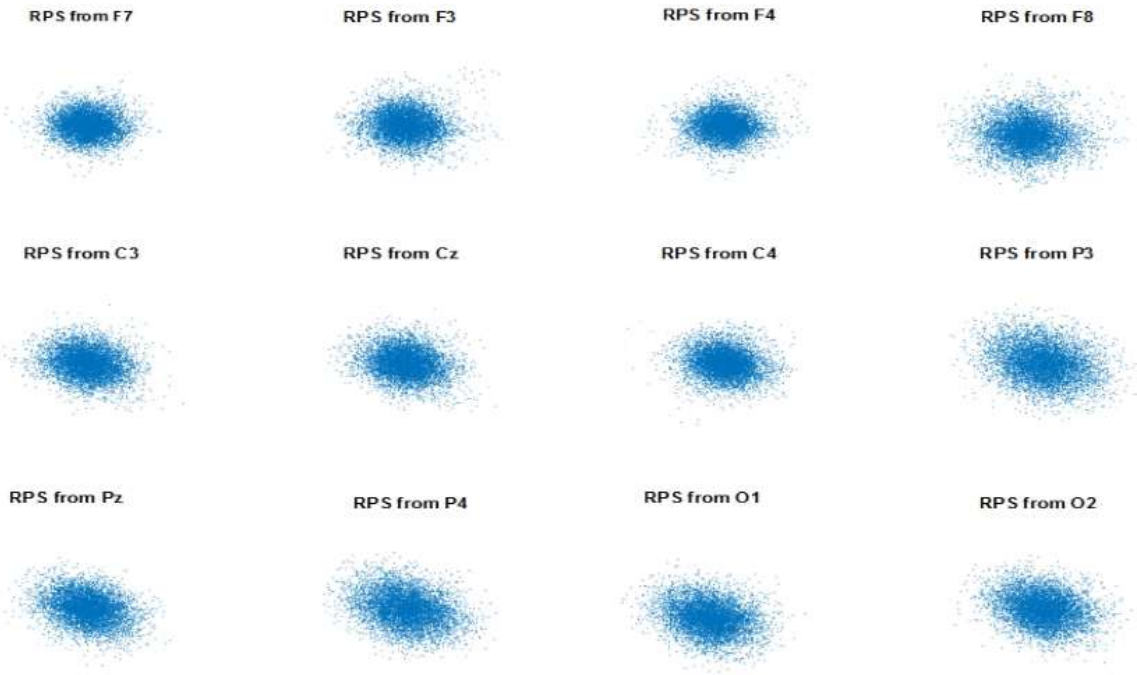

Figure 3. The RPS of 12- Normal EEG channels according to their locations.

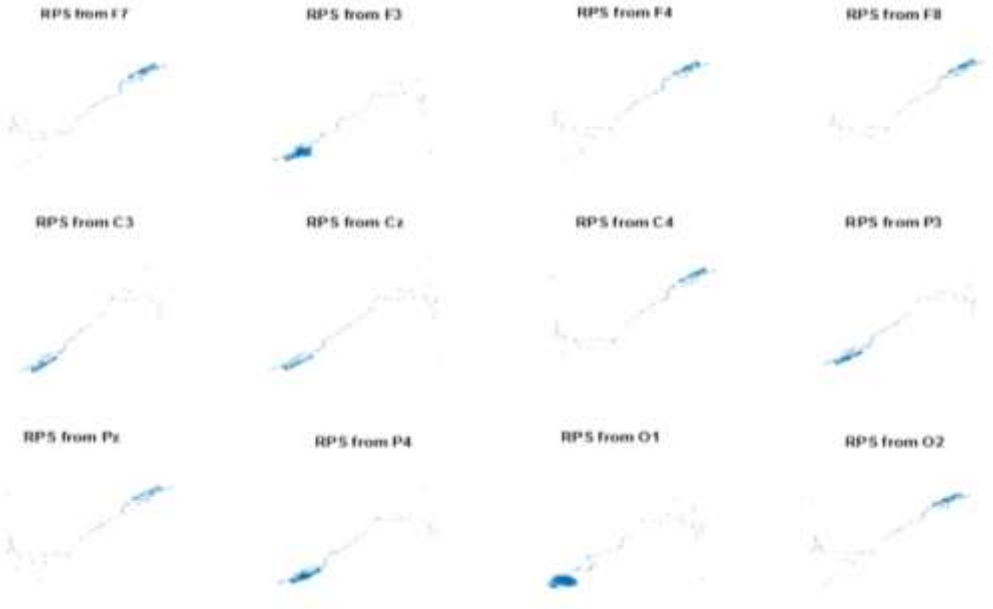

Figure 4. The RPS of 12- PD EEG channels according to their locations.

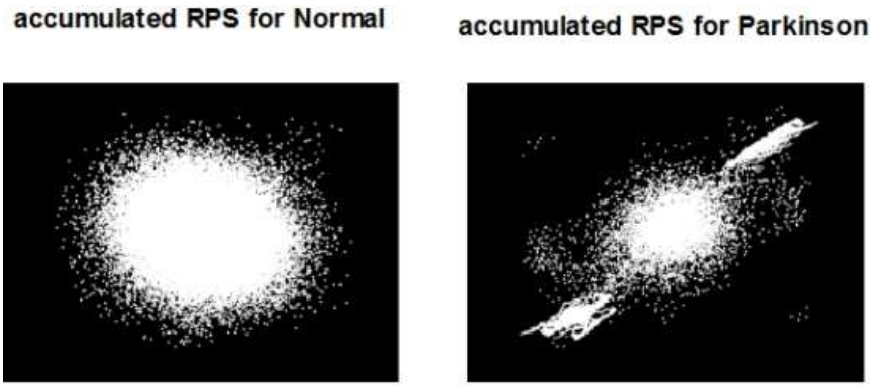

Figure 5. The accumulated RPS for samples from N and PD EEG classes.

Customized CNN Network

In this work, the ResNet-based depthwise combinational network which has a small but useful number of layers is proposed. It combines depth, strength, generalizability, interpretability, and rapid computing to get the correct results. Using a minimum number of ResNet's layers, this design solves the vanishing gradient problem that plagues deep neural networks, allowing for greater depth without sacrificing performance or training efficiency. This simplified technique retains deep networks' characteristics, such as powerful feature extraction and robust learning, while decreasing their complexity and computing cost. For binary classification tasks, the network balances depth for complicated patterns with generalizability across varied datasets by minimizing layers. Reduced complexity improves interpretability, making network decisions clearer. This approach allows faster calculation without losing accuracy. The RPS CNN network shows how a 5-layer efficient architecture can improve classification performance, training speed, and generalization, making it a useful tool for RPS image-based classification applications. Further details and analysis of the customized CNN network can be found in [39-40].

4. Results and Discussion

Various metrics can be employed to evaluate the algorithm's performance. Accuracy, sensitivity, specificity, precision, the F1 score, and the Matthews correlation coefficient (MCC) are among the most prevalent in the literature. Accuracy is the number of correct predictions divided by the total number of cases in the dataset. A test with high sensitivity can reliably tell if a condition is present, giving a high number of true positives and a low number of false negatives. This test is needed when not treating the illness could cause serious problems or when the medicine is very effective with few side effects. A test with a high level of specificity reliably leaves out human subjects who do not have the condition. This test results in many true negatives and only a few false positives. This test is crucial for subjects who are diagnosed with a disease that could lead to more medical tests, costs, stigma, and anxiety. Precision, also called "positive predictive value," is the percentage of relevant examples among the retrieved examples. Recall, which is also called sensitivity, is the percentage of relevant examples that were retrieved. Therefore, both precision and recall are dependent on relevance. The MCC is a contingency matrix technique for calculating the Pearson product-moment correlation coefficient between actual and predicted values. It is an alternative metric that is not affected by the problem of an unbalanced dataset. The F1 score is the harmonic mean of accuracy and recall [41].

Table 2 shows the classification results of the normal EEG signals. The performance of the average All channel RPSs outperforms any available classifier with all metrics achieving 100%. Additionally, F7 and P4 achieve 100% precision and specificity. However, P4 produces the lowest recall with 33% so F7 performs better than P4. On the other hand, F3 produces 0 TN, 100% precision, but 75% precision. On the contrary, the classifier performs well from specificity metrics for all channels with a minimum of 93.1%. While for MCC it goes from 49.1% at O1 and up to 100% for all channels. The minimum Fscore was 50 % at P4. Should single channel be used to analyze normal EEG signals using RPS deep learning classifier it will be channel F7.

Table 2. Result analysis of normal with distinct measures from different channels

Labels	$Prec_n$	$Reca_l$	$Spec_y$	F_{score}	MCC
All Channels	100.0	100.0	100.0	100.0	100.0
F7	100.0	83.3	100.0	90.9	90.2
F3	75.0	100.0	95.3	85.7	84.6
F4	71.4	83.3	95.3	76.9	73.7
F8	57.1	66.7	93.0	61.5	55.9

Labels	$Prec_n$	$Reca_l$	$Spec_y$	F_{score}	MCC
C3	57.1	66.7	93.0	61.5	55.9
Cz	71.4	83.3	95.3	76.9	73.7
C4	66.7	100.0	93.0	80.0	78.7
P3	80.0	66.7	97.7	72.7	69.7
Pz	66.7	66.7	95.3	66.7	62.0
P4	100.0	33.3	100.0	50.0	55.2
O1	60.0	50.0	95.3	54.5	49.1
O2	57.1	66.7	93.0	61.5	55.9

Table 3 tabulates the classification results for PD. As depicted from the table, average all channels RPSs performs very well with 100% for all metrics. Also, most of the channels were able to classify PD with minimum errors. Channels F3 and C4 were able to achieve 100% for all studied metrics. The worst result was linked with channel F8 with around 92% for all metrics.

Table 3. Result analysis of Parkinson's with distinct measures from different channels

Labels	$Prec_n$	$Reca_l$	$Spec_y$	F_{score}	MCC
All Channels	100.0	100.0	100.0	100.0	100.0
F7	96.2	100.0	95.8	98.0	96.0
F3	100.0	100.0	100.0	100.0	100.0
F4	96.2	100.0	95.8	98.0	96.0
F8	92.0	92.0	91.7	92.0	92.2
C3	100.0	96.0	100.0	98.0	96.0
Cz	100.0	92.0	100.0	95.8	92.2
C4	100.0	100.0	100.0	100.0	100.0
P3	100.0	96.0	100.0	98.0	96.0
Pz	96.2	100.0	95.8	98.0	96.0
P4	96.2	100.0	95.8	98.0	96.0
O1	96.0	96.0	95.8	96.0	91.8
O2	96.2	100.0	95.8	98.0	96.0

For the purpose of classifying Parkinson's disease, Matin et al. [26] conducted a scientific evaluation of 31 research publications. In Table 3 of their analysis, they discovered that accuracy metrics were accounted for and employed in 90.70% of the papers, while sensitivity was accounted for and employed in 69.77% of the studies, and specificity was accounted for and employed in 46.51% of the papers. It was determined that models that included at least two metrics were more significant than 90% of the articles that were examined. For instance, four articles that employed ANN had sensitivity and precision values exceeding 97%, three articles that employed CNN had accuracy, precision, and sensitivity values exceeding 99% (two of these references were based on the same study), and two references that employed CNN + RNN had accuracy, sensitivity, and precision values exceeding 93%. Models with at least two metrics that were more significant than 90% were identified in the 31 articles

that addressed the diagnostic problem of PD. The validation approach was implemented for these publications in order to determine the extent to which the model could generalize the results of blind tests. Cross-validation was the primary technique employed in nine of the twelve publications, while three papers partitioned the data into training, validation, and testing. The CNN and ANN models demonstrated the most superior performance [23]. Only one of the 31 papers in [23] reported a correct dataset 100% of the time. The metrics for the other dataset must still be provided [24]. In order to establish a baseline for the accuracy metric, the content of the studies that were intended to diagnose Parkinson's disease was evaluated, resulting in a value of 97.35 +/- 3.46%. This article introduces a novel algorithm that has achieved a 100% accuracy rate in the diagnosis of Parkinson's disease (PD) using fewer channels than previous studies. It is the sole algorithm to achieve this level of accuracy across all channels using a straightforward RPS CNN network. The other performance features were demonstrated to be both robust and stable. The classification procedure was repeated 100 times for additional investigation, and it maintained an accuracy of 99.8+/0.2%. The 12-electrode configuration was the only one used in the investigation. It is important to note that the EEG cleaning procedure and the number of channels did not affect Parkinson's disease diagnosis.

This research significantly improves the understanding and therapeutic strategies for Parkinson's disease. The automated and early identification of Parkinson's disease is achieved through the use of acoustic signal analysis and machine learning techniques in our proposed method. In order to conduct comprehensive screenings for Parkinson's disease, the methodology that has been devised provides a noninvasive and economically viable alternative to the current diagnostic procedures, which are both resource-intensive and time-consuming. This influential work of literature continues to have a profound impact on the healthcare industry, as it envisions a future in which medical practitioners will be able to advance through the use of cutting-edge diagnostic technologies that work in tandem. In order to accomplish this objective, we consistently ensure that patient health outcomes are enhanced and that interventions are delivered promptly.

This study has many limitations. First, electroencephalography (EEG) has intrinsic noise due to small muscle movements and ocular twitches that continue even during rest. During our examination, no noise artifacts were removed. Despite this study's high metrics, artifact removal may improve data consistency. Our analysis included channel data averaging to optimize the signal-to-noise ratio. This method may have reduced EEG data dimensionality, resulting in the loss of spatial information. Additionally, the study did not examine EEG recordings from different stages of Parkinson's disease. This would have revealed temporal abnormalities that could have been used to compare PD patients to healthy controls. In conclusion, this data shows a consistent effort to increase diagnosis precision. Despite these advancements, the detection and automation of Parkinson's disease for optimal results remain challenging. This work seeks to overcome these limitations and improve Parkinson's diagnosis.

5. Conclusions

In conclusion, this study provides a novel strategy for early diagnosis and understanding of Parkinson's disease (PD) using cutting-edge artificial intelligence and data processing. Using a custom-designed CNN, EEG data, DST, and RPS, the study obtained 99.8+/- 0.2% classification accuracy. This major result shows that this strategy can alter Parkinson's disease early detection, improving patient outcomes and quality of life. A big set of data from 168 people with Parkinson's disease and 39 healthy controls shows that EEG signals processed with phase dynamics are accurate and can be used with different data lengths and sample sizes. This versatility makes the procedure clinically useful and prepares it for future studies and healthcare applications. This approach examines motor symptoms and brain dynamics to understand PD's progression and therapy choices. To enhance Parkinson's disease diagnosis and treatment, longitudinal research and larger patient cohorts are needed to corroborate findings. Comparing the procedure to established clinical exams and imaging can further demonstrate its clinical utility. By improving early diagnosis and clinical decision-making, the discovery could minimize Parkinson's disease's financial and emotional burdens and improve patient care.

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