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A Novel Approach to Parkinson's Disease Progression Evaluation Using Convolutional Neural Networks

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ABSTRACT

Parkinson's disease (PD) is a devastating disorder with serious impacts on the health and quality of life for a wide group of patients. While the early diagnosis of PD is a critical step in managing its symptoms, measuring its progression would be the cornerstone for the development of treatment protocols suitable for each patient. This paper proposes a novel approach to digital PPMI measures and its combination with spirals drawings to increase the accuracy rate of a neural network to the maximum possible. The results show a well performing CNN model with an accuracy of 1(100%). Thus, the end-users of the proposed approach could be more confident when evaluating the progression of PD. The trained, validated, and tested model was able to classify the PD's progression as High, Medium, or Low, with high sureness.

KEYWORDS

CNN, Neural Network, Parkinson, Parkinson Progression, PPMI

1. INTRODUCTION

Individuals in their 60s are increasingly affected by neurological conditions. Parkinson's disease (PD) is the second most common neurological syndrome in the central nervous system (Benba et al. 2016a). There is a consensus among neurologists and researchers that Parkinson's is caused by aberrations in dopamine signaling in the brain; that is, the dopaminergic neurons fail to release enough signaling substance (dopamine) due to the demise of a significant percentage of them. Bradykinesia (slowness of movement), dysphonia (voice impairment), rigidity, tremor, and poor balance are common symptoms of PD that raise alerts regarding the loss of dopaminergic neurons in the substantia nigra of the brain (Diaz et al. 2022, Louis et.al 2015, Duffy, 2013), that is, the etiology of PD (Kouli et al., 2018). Multiple techniques have been used to detect PD at early stages. For instance, the accuracy of Magnetic Resonance Imaging (MRI) of the brain has increased; thus, MRI has been a part of PD diagnosis (Heim, et al. 2017, Fioravanti, et al. 2015). Physicians have visually and quantitatively interpreted MR images based on changes in brain structure and different types of tissues to identify

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PD (Tolosa et al.2021, Pyatigorskaya et al., 2018, Heim, 2017, Sterling et al. 2016, Fioravanti, 2015). Moreover, acoustic analysis of patients could help detect voice impairments, which is one of the signs of early PD (Fernández-García et al. 2021, Al-Fatlawi et al., 2016).

Certainly, each PD patient experiences dissimilar progression, cadence, occurrence, evolution and severity of symptoms (Raket et al., 2022), therefore, monitoring these manifestations is of great medical value in order to identify patients with a higher risk of rapid disease progression at early or at advanced stages of the disorder. The benefit of gauging the disease progression is to reassess the level of attention and monitoring required for these patients to cope with the aggressive evolution of their PD symptomatology. Consequently, this helps to ensure an acceptable level of quality of life, which requires careful adjustment of the PD's management plans.

Isolating potential markers that accelerate PD's progression could provide insights into the intricate mechanisms behind the manifestation and evolution of symptoms. Studying patients who experience faster worsening of PD, offers a golden opportunity to understand the disease and the factors contributing to such rapid progression. These factors might be amplified and thus easier to detect (e.g., brain connectivity networks, enzymes, proteins, and variations in metabolic paths). Cerebrospinal fluid (CSF) is often used to detect changes in the homeostasis of the central nervous system. Furthermore, the most accurate approach for determining the progression rate of PD is to estimate the deterioration status of specific brain networks using imagery (Sterling et al. 2016). However, motor and non-motor symptoms evaluation is easier and more cost effective. For instance, Unified Parkinson's Disease Rating Scale (UPDRS) offers accurate alternatives for rating PD progression; however, computer-assisted technologies can be used to monitor patients and their motor impairments, regardless of the probable uncertainty in the clinical ratings (Lu et al. 2021). Furthermore, motor symptoms progression differs from patient to patient; thus, it can be used as a metric to monitor the haste (rapid or slow) of the progression of the disorder. Roede et al. (2013) reported considerable variations in the annual worsening rate between the rapid (5.95) and slower (1.45) groups using UPDRS-III. Moreover, Fereshtehnejad et al. (2015) suggested that orthostatic hypotension, a rapid eye movement sleep behavior disorder, and signs of cognitive impairment could signal the decline of motor symptoms in patients. Undoubtedly, non-motor symptoms attributed to PD have an influence on patients and must be monitored and treated. For instance, cognitive impairment can be predicted based on the patient's age, presence of olfactory disturbances, sleep disturbances, and CSF biomarkers, as suggested by Schrag et al. (2017). In recent years, much attention has been given to the development of diagnostic systems based on artificial intelligence concepts, such as machine learning, and data mining to detect PD. A variety of data sources have been available to provide valuable datasets, such as handwritten patterns, speech recordings, voice signals, physiological signals, and collected data from wearable sensors for gait and others. These datasets can be used to predict PD using neural networks (Liaqat et al. 2019a; Liaqat et al. 2019b; Al-Fatlawi et al., 2019; Parisi et al., 2018 ; Naranjo et al.,2017a; Guruler et al. 2017 ; Naranjo et al., 2016; Sakar et al., 2013 ; Tsanas et al., 2012; Rigas et al. 2012; Das et al., 2010; Little et al. 2009). For instance, speech recordings, as a dataset, have been the target of multiple techniques used to detect PD. Little et al. (2009) applied a support vector machine (SVM) to replicate data from 31 subjects, which, resulted in 91.4% detection accuracy. Furthermore, complex-valued artificial neural networks with k-means clustering and feature weighting approaches had been applied to the same dataset, which increased the classification accuracy to 99.52% (Orozco-Arroyave et al. 2016). Despite the promising reported results, the issue is that the dataset is imbalanced; thus, most machine learning algorithms, which are very sensitive to imbalanced classes, led to flawed outcomes. Moreover, most studies used the conventional k-fold cross-validation approach. This ensured that all observations from the original dataset had the chance to appear in the training and test sets. However, this causes a subject overlap, which is a major issue. Subsequently, new balanced datasets had been created, such as the training and testing databases collected by Sarkar et al. (2013). The authors applied the k-nearest neighbor model and SVM classifiers to these new datasets, which surprisingly resulted in a 55% accuracy rate.