Explainable Prediction of Parkinson's Disease from Resting-State Functional MRI Using Hybrid 3D CNN-LSTM Model

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***Abstract*—**

***Index Terms*—Parkinson's disease, Deep learning, Early detection**

I. Introduction

Parkinson's disease (PD) is a prevalent neurological condition characterised by impairments in muscle function. Bradley-like tremors, muscle rigidity, and bradykinesia result from the effects of this condition on speech, movement, and posture [1]. Neuronal death precipitates the condition, which is characterised by reduced dopamine levels in the brain. Motor activity that is ineffective is the result of impaired synaptic transmission brought on by insufficient dopamine [2].Hand tremors, rigidity in the limbs, and challenges with balance and gait are some of the possible manifestations of tremors. Movement-related (or motor) symptoms and non-motor symptoms comprise the two main categories of Parkinson's disease (PD) symptoms. Given the absence of a known remedy for Parkinson's disease (PD), individuals affected by this condition must depend on timely detection and specialized treatment to impede the advancement of the ailment. In stage 0 of Parkinson's disease (PD), 90 percent of individuals with vocal cord impairment exhibit symptoms. Furthermore, vocal dysfunction can be easily measured and is also encompassed by the field of remote medicine, commonly known as telemedicine [3]. Instead of engaging in a physical visit to a doctor, patients have the option to conveniently do a test at home or utilize their phones to record audio. Dysphonia and dysarthria are frequently observed indications of voice modulation.

To assess impairment realistically, patients can undergo running speech tests or be instructed to sustain the pitch of a single vowel for as long as possible. This method is referred to as sustained phonation. Phonation tests can be used to diagnose Parkinson's disease at stage 0. Timely detection enables healthcare practitioners to impede the advancement of Parkinson's disease (PD) by reviving dopamine-generating neurons in the brain by therapeutic interventions or deep brain stimulation [6]. At present, Parkinson's disease lacks a known remedy owing to its intricate nature. However, early identification and suitable therapy can mitigate patients' tremors and imbalance symptoms, enabling them to return to their normal daily routines.

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II. Literature Review

Prior studies have utilised MRI scans, movement analysis, and genetic data to produce prognostications concerning Parkinson's disease. Nevertheless, there is a dearth of research that especially focuses on the early detection of auditory impairment. For example, Bilal et al. [7] utilised a Support Vector Machine (SVM) model to predict the onset of Parkinson's Disease (PD) in elderly adults by analysing genetic data. The researchers acquired a training accuracy of 0.889 with an SVM model, however this specific research report describes an enhanced SVM model that obtained an accuracy of 0.9183. Furthermore, these findings validate the superiority of auditory data classification over genetic data classification in the context of Parkinson's disease (PD). The user's text is "[8]". Raundale, Thosar, and Rane (2018) did a study where they trained a Random Forest classifier to forecast the intensity of Parkinson's disease in older people. The researchers employed keystroke data from the UCI telemonitoring dataset for this objective. Cordella et al. [9] utilised audio data to categorise individuals with Parkinson's disease (PWP) in their research. Nevertheless, it is important to acknowledge that their models rely extensively on the use of MATLAB. The research we conduct makes use of Python-based open-source models that are characterised by their efficiency in terms of memory usage and speed. The majority of studies, including the study conducted by Ali et al. [10], concentrates on the application of ensemble deep learning models to analyse phonation data in order to forecast the progression of Parkinson's disease. This study highlights the need of utilising deep learning methods for the identification of Parkinson's disease. The paper demonstrated a deficiency in the process of selecting relevant features, which may have greatly enhanced the efficiency of deep neural networks (DNNs). This research utilises Principal Component Analysis (PCA) to examine 22 variables and determine the seven main speech modes for the identification of Parkinson's disease (PD). In order to decrease reliance on wearable devices for the diagnosis of Parkinson's disease (PD), Huang et al. [11] undertook a study in which they trained a traditional decision tree utilising 12 complex speech features derived from the MDVR-KCL [12] dataset. Wodzinski et al. [13] chose to use images of audio data instead of training a ResNet model specifically on the intricacies of audio frequency. Wroge et al. [14] employed an unbiased machine learning algorithm to reduce the impact of subjective assessments provided by doctors when predicting Parkinson's disease (PD). Nevertheless, their research revealed a peak accuracy of 85

In a study referenced as [15], four classifiers, specifically Decision Trees, Regression, DMneural, and Neural Networks (NN), were compared to detect Parkinson's disease. The results indicated that the NN algorithm attained the highest degree of precision, at 92.9 percent. The citation-referenced researchers [16] identified Freezing of Gait (FOG), a dependable indicator for Parkinson's disease patients with an elevated risk of collapsing, by employing an extended short-term memory algorithm. According to empirical evidence, LSTM is more effective than SVM at detecting FOG. Vigilant observation of the initial phases of Parkinson's disease, referred to as the prodromal or premotor stage, is imperative for the timely detection of the condition [17], [18]. This premotor stage is distinguished from others by the presence of Rapid Eye Movement (REM) sleep behavior disorder (RBD) and anosmia (olfactory loss) [17].

In their comprehensive methodology, Wang et al. [19] distinguished between individuals who had been diagnosed with Parkinson's disease and those who were asymptomatic. The researchers classified a dataset containing 401 vocal biomarkers using twelve distinct machine learning models. A bespoke deep learning model denoted as DEEP, was developed and demonstrated a remarkable accuracy in the classification of 96.45 percent. However, due to its significant memory requirements, the device became economically unfeasible. Alkhatib et al. [20] were able to accurately distinguish the shuffling movements of patients with Parkinson's disease (PD) by employing a linear classification model in their investigation. They achieved a remarkable accuracy rate of 95 percent. The main focus of their research revolved around the patients' gait. Their suggestion is to incorporate audio and sleep data into future studies to enhance the results. Ricciardi et al. [21] performed a spatial-temporal analysis on magnetic resonance imaging (MRI) scans of the brain. An analysis was performed to detect Mild Cognitive Impairment (MCI) in patients with Parkinson's Disease (PWP) using the K-Nearest Neighbours (KNN), Random Forest, and Decision Trees algorithms.

In a work conducted by A. U. Haq and colleagues [22], L1-support SVM was used as a vowel phonation dataset for patients with neurological diseases. Notably, feature identification was not included in the analysis. The research carried out by Aditi Govindu and her team, published in Procedia Computer Science 218 (2023) 249–261, centred on a group of persons aged between 46 and 85 years. The study undertaken by the author, as outlined in Procedia Computer Science 00 (2019) 000–000, overlooks the incorporation of healthy persons in the younger age group. In their study, Mei et al. [23] emphasise the significance of machine learning in identifying Parkinson's disease (PD), pointing out that relying solely on subjective evaluation by doctors may lead to the omission of minor non-motor symptoms. The authors' research analyses 209 studies, investigating dataset features, machine learning algorithms used, and the resulting outcomes. As stated in reference [24], the optimal classifier for detecting Parkinson's disease (PD) was determined to be a blend of Decision Trees, Regression, DMneural, and Neural Networks (NN). This combination achieved a maximum accuracy of 92.9 percent, which was achieved by the NN method. Recently, AI-based techniques have gained popularity in diagnosing PD due to their capacity to handle vast volumes of data and achieve significant dependability without imposing limitations on the data distribution [25,26]. The authors employed a long short-term memory technique [25] to identify Freezing of Gait (FOG), a dependable indicator of individuals with Parkinson's disease who are prone to falling. Empirical data indicates that Long Short-Term Memory (LSTM) outperforms Support Vector Machines (SVM) in terms of detecting FOG.

III. Methodology

A. Dataset Description

We are using publicly available datasets from the National Institute for Research and Development in Informatics in Romania, which are relevant to our inquiry on Parkinson's disease. The dataset consists of images obtained from Magnetic Resonance Imaging (MRI) scans given to individuals with Parkinson's disease and healthy controls of the same age. Images from structural and functional magnetic resonance imaging (sMRI and fMRI) make up the dataset. A detailed examination of the characteristics of the structure and function of the brain is made feasible by the use of magnetic resonance imaging, or MRI.

B. Preprocessing of Data

To address issues like noise reduction and normalization, for example, we start our multi-pronged approach to our study with meticulous preparation. After that, we employ a variety of advanced techniques for data processing. Any motion artifacts in the data are being corrected by us using the motion correction approach. Additionally, we are smoothing the fMRI pictures with Gaussian filters. Additionally, every pre-processed fMRI image was matched to a similar pre-processed structural T1 image of the same individuals. Furthermore, these pictures underwent resampling and were registered to the industry-standard MNI152 space. As part of a comprehensive neuro-imaging workflow, the process begins with the acquisition of functional magnetic resonance imaging (fMRI) and structural magnetic resonance imaging (sMRI) data from participants. It makes the gathering of precise anatomical and functional data about the brain possible. To enhance the quality of the functional magnetic resonance imaging (fMRI) data, pre-processing techniques such as slice-timing correction and spatial normalisation are applied. With pre-processed functional magnetic resonance imaging (fMRI) data, dictionary learning techniques are applied with the aim of extracting temporal patterns to improve the data set for further analysis.

C. *Model Development and Experimental Setup*

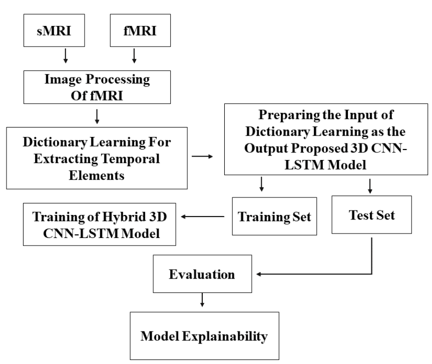

Fig. 1. Work Flow of Model

A hybrid three-dimensional model is incorporated into the workflow. This model combines Convolutional Neural Networks (CNN) for the extraction of spatial features and Long Short-Term Memory (LSTM) networks for the modeling of temporal-dependent relationships. The dataset is then segmented into training and validation subsets, and the model is trained using a specific training set that has been specified for that purpose. To evaluate the generalization performance of the model, testing is performed on a separate test set. To determine how useful the model is, evaluation criteria such as accuracy and precision are brought into play. To better understand and pinpoint the workability of the proposed model, we are using explainable AI tools such as - GRADCAM to explain what and how the black box model is predicting.

IV. Result Analysis

V. Future Work

VI. Conclusion

Acknowledgment

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