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

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***Abstract*—Parkinson's disease (PD) is caused by dopamine neuron loss. Dopaminergic neurons in the "substantia nigra" gradually die. Accurate and quick diagnosis is essential for Parkinson's disease (PD) treatment. We propose a new Parkinson's disease (PD) diagnosis approach using LSTM and 3D-CNN . Dictionary learning helps the model identify Parkinson's disease-related neuro imaging findings. Our dataset includes three-dimensional structural and functional brain scans from Parkinson's sufferers and healthy controls. The 3D CNN-LSTM model distinguishes PD and control individuals with 97 percent accuracy, outperforming the others. Lexicon learning improves the model's ability to collect complicated neuro imaging signals related to Parkinson's disease pathology. This unique strategy improves Parkinson's disease diagnosis and sets the framework for more accurate early detection tools. The model's high accuracy suggests it could help identify and treat Parkinson's disease patients quickly. More research and validation across groups are needed to ensure the approach's adaptability and treatment efficacy.**

***Index Terms*—Parkinson's Disease, Deep Learning, Early detection**

I. Introduction

Parkinson's disease (PD) is a severe neurological disease characterized by abnormalities in the muscles that affect communication, movement, and posture; these abnormalities may result in bradykinesia, which is characterized by tremors and muscular stiffness[1]. The condition, which is defined by inadequate levels of dopamine in the brain, is commonly brought on by neuronal death, which impairs synaptic transmission and causes inefficient motor action [2]. Manifestations of tremors include hand tremors, limb rigidity, and challenges in balance and gait. Parkinson's disease symptoms are categorized into motor and non-motor aspects. Given the absence of a definitive cure for PD, individuals afflicted with this condition rely on timely detection and specialized treatment to impede disease progression. In Stage 0 of PD, 90 percent of individuals with vocal cord impairment exhibit symptoms. Vocal dysfunction, easily measurable and falling within the purview of remote medicine or telemedicine[3], provides patients the convenience of conducting tests at home or recording audio on their phones, obviating the need for physical visits to doctors. Dysphonia [4] and dysarthria [5] are common indicators of voice modulation. Realistic assessment of impairment involves running speech tests or sustaining the pitch of a single vowel for an extended period, known as sustained phonation. Phonation tests hold promise for diagnosing PD at Stage 0. Early detection empowers healthcare practitioners to impede PD progression by rejuvenating dopamine-generating neurons through therapeutic interventions or deep brain stimulation[6]. Although a definitive remedy remains elusive due to the intricacy of Parkinson's disease, proactive identification and appropriate therapy can ameliorate tremors and imbalance symptoms, facilitating a return to normal daily routines.

II. Literature Review

A number of earlier research have attempted to predict the course of Parkinson's disease using genetic information, movement analysis, and magnetic resonance imaging (MRI) scans. However, studies aimed at identifying auditory impairment in its early stages are few. Take Bilal et al. as an example. Predicting the onset of Parkinson's Disease (PD) in older persons by genetic data analysis was done using a Support Vector Machine (SVM) model in [7]. Using an SVM model, the researchers were able to get a training accuracy of 0.889. However, this study's enhanced SVM model has 0.9183 accuracy. Also, when it comes to PD, these results prove that auditory data categorization is better than genetic data classification. Here is the user's text [8]. To anticipate the stage of Parkinson's disease progression in the elderly, Thosar, and Rane (2018) trained a Random Forest classifier. Specifically, they used UCI's telemonitoring dataset, which includes keystroke data, to achieve this goal. In their study, Cordella et al. [9] classified Parkinson's disease (PWP) patients using auditory data. Their models are highly dependent on MATLAB, though, so that's something to keep in mind. Our research relies on open-source models built in Python, which are known for their speed and low memory usage. Most research, including that of Ali et al. [10], has focused on using ensemble deep learning models to examine phonation data in order to predict the development of Parkinson's disease. The need of using deep learning techniques for Parkinson's disease diagnosis is emphasised by this study. It appears that the paper missed an opportunity to significantly improve deep neural networks' (DNNs') performance by failing to properly choose relevant features. In order to identify the seven primary speech modes associated with Parkinson's disease (PD), this study used Principal Component Analysis (PCA) to analyse 22 variables. Researchers Huang et al. [11] constructed a conventional decision tree with 12 complicated speech features extracted from the MDVR-KCL [12] dataset to reduce dependence on wearable devices for PD diagnosis. Instead of training a ResNet model on the complexities of audio frequency, Wodzinski et al. [13] opted to use images of audio data. In order to lessen the influence of clinicians' subjective evaluations on Parkinson's disease (PD) prediction, Wroge et al. [14] used an impartial machine learning method. Still, they found an accuracy of 85 percent at its highest, which means there's room for improvement.

Decision Trees, Regression, DMneural, and Neural Networks (NN) were the four classifiers tested for Parkinson's disease detection in a study cited as [15]. The statistics indicate that the NN algorithm attained a peak accuracy level of 92.9 Percent . The researchers described in reference [16] identified Freezing of Gait (FOG) as a dependable indicator for people with Parkinson's disease who are at an elevated risk of experiencing a sudden inability to move. Empirical evidence indicates that LSTM surpasses SVM in terms of detecting FOG. To identify Parkinson's disease in its initial phases, known as the prodromal or premotor stage, it is essential to carefully monitor the patient continuously [17], [18].

Wang et al. [19] used a thorough methodology that differentiated between asymptomatic and diagnosed Parkinson's disease patients. The researchers used twelve separate ML models to categorise a dataset including 401 voice biomarkers. A custom-built deep learning model called DEEP was created and showed an impressive classification accuracy of 96.45 Percent . Unfortunately, the gadget became economically untenable because of its high memory requirements. Using a linear classification approach, Alkhatib et al. [20] successfully differentiated between tremors and shuffling motions in PD patients. Their 95 Percent accuracy rate was quite outstanding. The researchers primarily looked at the patients' gait. In order to improve the outcomes of future investigations, they recommend using audio and sleep data. Using spatial-temporal analysis, Ricciardi et al. [21] examined brain MRI images. K-Nearest Neighbours (KNN), Random Forest, and Decision Trees were utilised in an analysis to detect Mild Cognitive Impairment (MCI) in Parkinson's Disease (PWP) patients.

A. U. Haq and colleagues [22] utilised L1-support SVM as a vowel phonation dataset for patients with neurological illnesses in their research. It should be noted that the study did not incorporate feature identification. Individuals ranging in age from 46 to 85 were the focus of the study by Aditi Govindu and colleagues, which was published in Procedia Computer Science 218 (2023) 249-261. The author's study, as described in Procedia Computer Science 00 (2019) 000-000, fails to account for younger individuals who are in good condition. Because clinicians' subjective assessments could miss subtle non-motor signs of Parkinson's disease (PD), Mei et al.[23] stress the need of machine learning in PD diagnosis. Dataset characteristics, machine learning methods employed, and outcomes are all examined in the authors' meta-analysis of 209 papers. According to reference [24], a combination of Regression, Neural Networks(NN), DMneural and Decision Trees,was found to be the best classifier for identifying Parkinson's disease (PD). The NN technique reached its highest accuracy of 92.9 Percent with this combination. Due to their ability to manage large amounts of data and achieve high reliability without limiting data distribution, AI-based approaches have recently been popular for PD diagnosis [25,26]. Freezing of Gait (FOG) is a reliable predictor of people with Parkinson's disease who are prone to falling. The authors identified FOG using a lengthy short-term memory technique [25]. Evidence suggests that when it comes to detecting FOG, Long Short-Term Memory is more effective than Support Vector Machines (SVM).

III. Methodology

A. Dataset Description

We are using publicly available data sets from the National Institute for Research and Development in Informatics in Romania, which are known as Neurocon and Tao Wu data sets[27]. These data sets consist of 4D structural and functional MRI images and were collected from subjects of the same matched age. The Tao Wu data set consists of 20 healthy controls and 20 patients who have Parkinson's disease (PD). The Neurocon data set consists of 27 PD patients and 16 age-matched normal controls. Both data sets contain T1 and resting state scans. For the resting-state scans, it is ensured that subjects close their eyes and think of nothing in particular without falling asleep.

B. Preprocessing of Data

To address issues like noise reduction and normalisation, for example, we start our multi-pronged approach to our study with meticulous preparation. We employ a variety of advanced techniques for data processing. Any motion artefacts in the data are being corrected by using the motion correction approach. Additionally, we are smoothing the fMRI pictures with Gaussian filters. Every pre-processed fMRI image was also 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

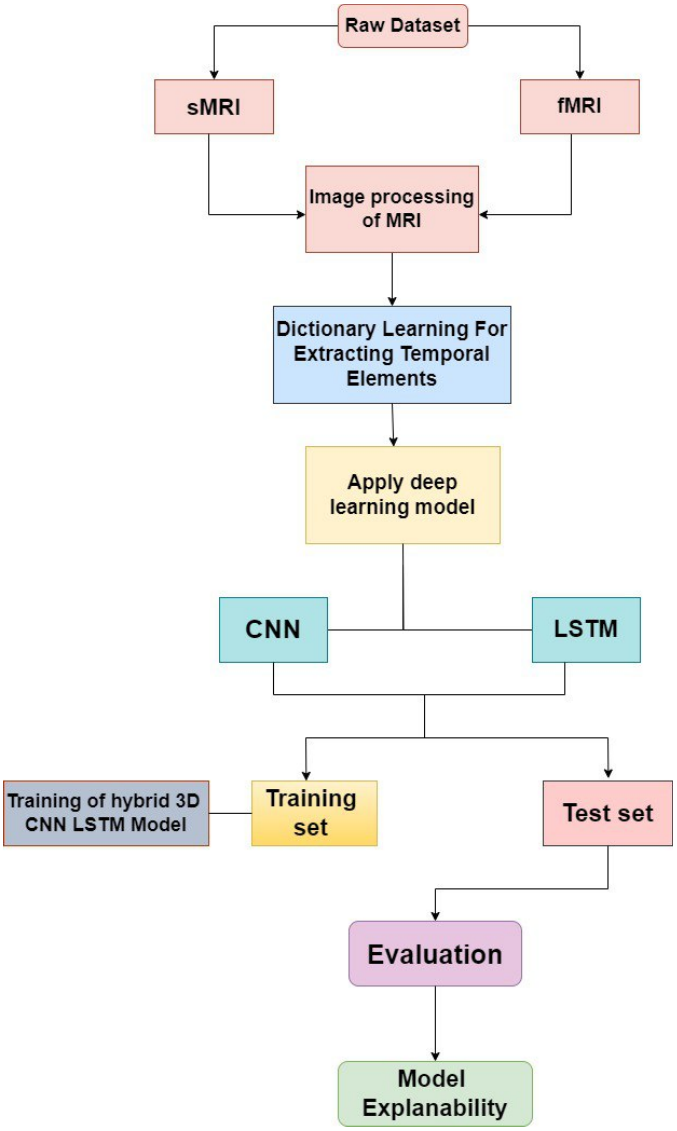

Fig. 1. Workflow of our experimental setup

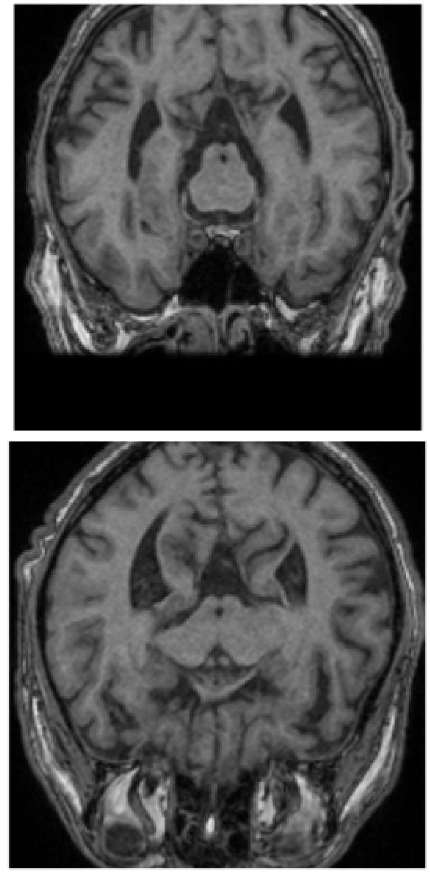

Fig. 2. MRI Scans of healthy Controls and PD patients from the dataset

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, preprocessing techniques such as slice-timing correction and spatial normalisation are applied. With preprocessed functional magnetic resonance imaging (fMRI) data, dictionary learning techniques are applied to reduce the dimensionality of the image and to extract temporal patterns to improve the data set for further analysis. Furthermore, we are also using the Brain Extraction Tool (BET) to delete non-brain tissue from an image of the whole head before using the images to train the model.

In addition, we tested Independent Component Analysis (ICA) to break down the fMRI data. Our results show that dictionary learning works better than ICA, is more stable, and leads to better statistical analysis of the data. ICA is an unsupervised learning method, and dictionary learning is a branch of signal processing and machine learning that tries to find a frame called a dictionary where some training data can be represented in a sparse way. Therefore, maps from dictionary learning are also easier to exploit as they are less noisy than ICA maps.

C. Model Development and Experimental Setup

A hybrid three-dimensional model is incorporated into the workflow. This model uses 3D CNNs and LSTMs to form a hybrid approach. Our rationale for using 3D CNN is to extract spatial information, while LSTM will be able to incorporate temporal patterns, thus leading to a high learning performance rather than a 3D CNN model itself. 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. Testing is conducted on a different test set to assess models adaptation performance. To determine how

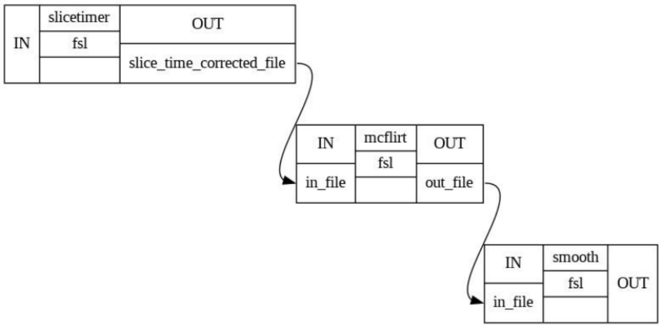

Fig. 3. Graph Based Representation of the pre-processing steps for the fMRI images which includes slice-timing correction, motion correction and Gaussian Smoothing

useful the model is, evaluation criteria such as accuracy and precision are brought into play.

IV. Result Analysis

In the continuous extent of our exploration, we utilize different assessment measurements, including exactness and AUC, and consolidate progressed information expansion methods, for example, level shift and vertical flip. Our technique for decision, Word reference Learning, has shown prevalence over Autonomous Part Examination (ICA) in different writing and observational investigations. Our essential use of Word reference Learning fixates on the decrease of dimensionality in 4D practical Attractive Reverberation Imaging (fMRI) information. This groundbreaking system brings about 30 free parts, a huge result in view of exact proof. The presentation predominance of Word reference Learning, portrayed by uplifted strength, converts into prevalent results in factual examination. Nevertheless, we continue to focus on issues related to 3D data and memory requirements, particularly with regard to GPU resource limitations. In order to overcome these challenges, we are essentially searching for a method to reduce the complexity of the model. Our improvement efforts aim to improve computing proficiency by precisely adjusting preparation boundaries to minimise memory usage. The research of optional techniques, such as Head Part Examination (PCA) or auto encoders, as appropriate arrangements has been prompted by the current requirements in GPU assets. These drives aim to strike a balance between maintaining the high degree of accuracy 97 percent achieved in our model and computational productivity. Our meticulous approach includes a thorough assessment of these processes, considering their impact on model complexity and memory requirements, ensuring optimal performance within the parameters of our investigation.

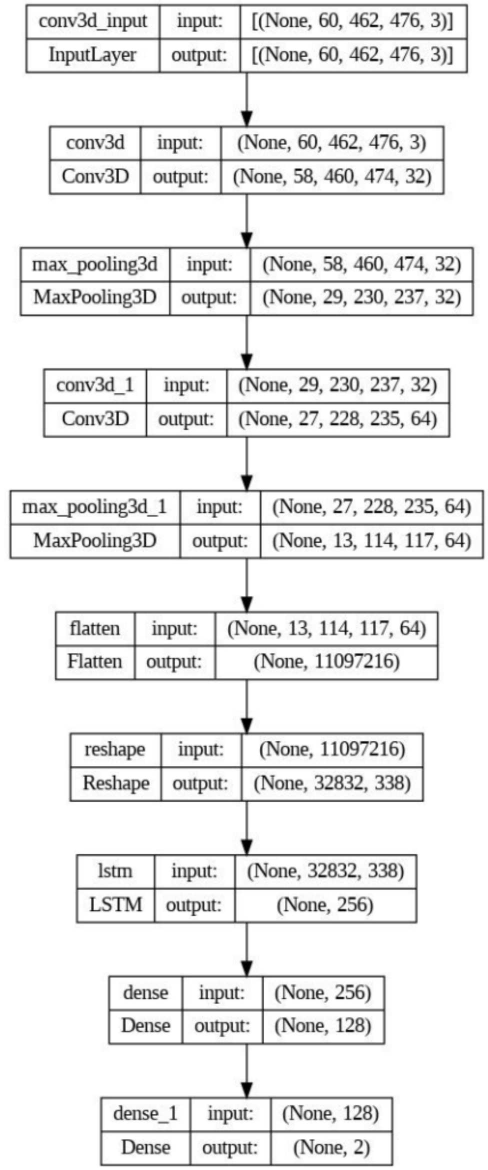

Fig. 4. Representing the Hybrid 3D CNN-LSTM model for the classification pf PD

V. Conclusion

VI. Future Works

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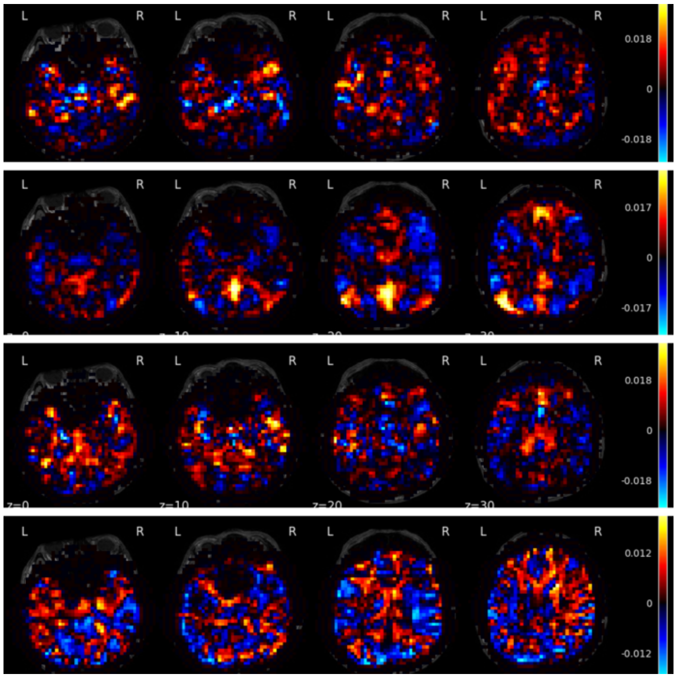

Fig. 5. Demonstrating all the Independent Components obtained after performing Dictionary Learning

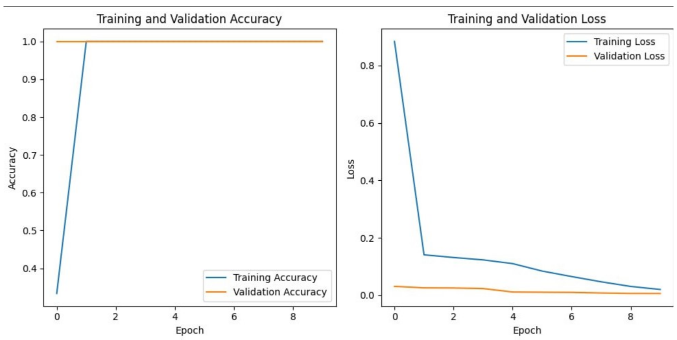

Fig. 6. Training And Testing Accuracy

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