Deep Learning based Neuroimaging analysis for Parkinson's disease detection

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***Abstract*—Parkinson's disease (PD) is the second most prevalent neurodegenerative disorder affecting more than 10 million people globally. Being an incurable disease, its onset prediction and analysis is crucial. Deep learning techniques have been progressing significantly towards neuroimaging and other medical analyses. In this study, we leverage the use of various Convolution Neural Network models such as 2D-CNN, VGG16, ResNet50 and LeNet-5 to classify the intricate functional Magnetic Resonance Imaging(fMRI) scans for distinguishing the Parkinson's Disease affected brains from healthy ones. By achieving the highest accuracy of 99.70%, this endeavour concluded that CNN architectures have the prospect to draw out extensive discerning features and novel biomarkers from complex clinical data and therefore has the competence to be beneficially utilized to a greater extent in more advanced systems.**

***Index Terms*—Neuroimaging, Parkinson, Deep Learning, CNN**

I. Introduction

Explorations concerning Parkinson's disease are being carried out all around the world. The unpredictability of this disease has lead to several attempts for the most standardised solution. This paper, aims to understand and answer the following questions:

1) What are the challenges involved in the prediction of Parkinson's disease?
2) What are the proposed methodologies for onset detection?
3) What can be improved to introduce a more reliable system?

Parkinson's disease(PD) is a neurodegenerative disorder that affects the patient's movement and coordination. It occurs in an area of the brain structure called Substantia Nigra(SN) where the dopamine-producing nerve cells (neurons) are either impaired or dying due to damage.

The Substantia Nigra is located in the basal ganglia in the midbrain region. It plays a dominant role in producing dopamine and influences the central nervous system. It is responsible for motor planning, cognitive abilities, learning and control. Dopamine is a neurotransmitter through which the brain cells interact i.e. channel signals through various sections of the brain. It is a prime molecule involving physiological and neurological actions. It contributes significantly to our mood, sleep, stress and also decision making.

Parkinson's disease also leads to the loss of another chemical(neurotransmitter) called norepinephrine or noradrenaline. It is the stress hormone that is liberated primarily from the ends of sympathetic nerve fibres and oversees some autonomic functions such as breathing and blood pressure. The depletion of this hormone triggers several non-motor symptoms of the disease. [2] discussed that The study of viruses and their genetics has been an opportunity as well as a challenge for the scientific community. The recent ongoing SARSCov2 (Severe Acute Respiratory Syndrome) pandemic proved the unpreparedness for these situations.

The most common symptoms of Parkinson's disease include:

1) Tremor: It is the shaking movement that generally arises in one hand or leg and eventually progresses to both sides of the body. A resting tremor can also appear in the jaw, mouth or tongue. It aggravates with stress.
2) Bradykinesia: It is the slowness of movement caused as a consequence of stagnant transmission of the brain's signals for various actions. It is a highly unpredictable symptom and rapidly incapacitates. One example can be the drag of feet while walking.
3) Muscle rigidity: It is the ineptitude of body muscles to ease out naturally. It stems from the lack of control over tensing and relaxation of muscles, leading to the inability to move about freely. It may also give rise to aches or pains in the affected muscles limiting the scope of motion.
4) Speech: Speech may be rapid, slurred or soft in tone. There could a slight stutter or hesitance in speaking. The pitch may become monotone.

5) Facial expressions: There may be difficulty in smiling or blinking normally leaving a deadpan expression on the face.

The diagnosis of Parkinson's disease can be quite complex. The many symptoms, as mentioned earlier, vary largely in patients and in some cases, they may not be certain until the mid-stage at all. While there exist several diagnostic tests for onset prediction of disease, such as spiral tests, GAIT analysis, speech-based assessments, etc., due to this uncertainty of symptoms not being present in all patients, it brings about a need for a more standardized prediction system.

Neuroimaging, which refers to brain-related medical imaging is a highly reliable and so-far the only analysis that assists in the diagnosis of Parkinson's disease for all possible patients. Imaging tests such as Magnetic Resonance Imaging(MRI) in functional and resting states, along with DaT scan can extract potential biomarkers that would ascertain the disorder. Deep learning methods that can replicate the biological neural networks, specializing in visual imagery analysis present a definitive solution to extracting all the possible features for such complex diagnoses.

II. Related Works

A. Phonation Analysis

In [1] a pioneering approach of using Principal component analysis (PCA) with data partitioning in a system that enables a voice-recording module with cloud web services is introduced. The dataset is based on several auditory characteristics. The research exhibited the highest accuracy of 85.0% for SVM with Gaussian. By combining classifiers and leveraging data partitioning, a 90.3% accuracy is seen for weighted k-NN classifiers model.

In [3] an attribute called Energy direction which is centred on empirical mode decomposition (EDF-EMD) is employed. EMD was used to decompose voice waves and obtain Intrinsic Mode Functions (IMFs). Sakar and CPPDD datasets are availed for the verification of proposed features. The dataset-Sakar had the best average resulting accuracy of 96.54%, while the dataset-CPPDD had that of 92.59%.

[3] presents a new speech characteristic to make a distinction to identify Parkinson's disease affected patients. Expanding the lines of research work in empirical mode decomposition(EMD)-based features, this study proposes intrinsic mode function cepstral coefficient (IMFCC). Two different datasets are considered and the effects on accuracy depending on the stated feature is observed to be considerably higher. The increase is found to be 10-20% more than those models that did not use this feature in their classification analysis.

Study [5] demonstrates the Extra Tree Classifier that had the highest average precision of 89% on the Audio-Visual Emotion Recognition Challenge (AVEC) features and a high precision of 85% on the GeMaps dataset. For the Gradient Boosted Decision Tree and Artificial Neural Network, the AVEC features provided the highest overall accuracy.

In [16], the challenge of auditory inconsistency among the operational and trained environments induced primarily by deterioration in test waveforms is addressed. The research findings leveraging voice signal recordings from the mPower mobile training dataset across diverse degrading circumstances illustrates the competence of quality gauging methods in the selection of a suitable boosting technique and as a result presents an increased accuracy of Parkinson's disease detection

B. Handwriting and Spiral Tests

Study [7] worked on the handwriting tests obtained using Wacom Intuos Pro graphic tablet. The kinematic, mechanical, and spatial interrelation characteristics were acquired. One-way analysis of variance (ANOVA) method was used to filter out the essential features. The Hoeffding classification and FarthestFirst clustering algorithms conferred 98.36% accuracy.

In [7], Along with the traditional Static Spiral Test, a Dynamic Spiral Test (DST) is applied on the Hand-Written (HW) dataset. The optimiser used for CNN is Stochastic Gradient Descent. DST and SST are incorporated as input for the model performance estimate method. The 10-fold and Leave One Out Cross-Validation (LOOCV) are compared where the latter had a lower accuracy. The suggested approach gave 88% accuracy value.

[9] introduced a Fuzzy recurrence plot (FRP) methodology to obtain grayscale texture images from time-series signals of DST and SST. Features are drawn out using AlexNet and GoogleNet. The testing is conducted using the KNN and SVM algortihms. The highest accuracy is observed to be 0.94 while the F1 score is 0.95.

In [14], the paper presented a multistage classifier approach based on both spiral and wave tests. The dataset was obtained from Kaggle and Convolutional Neural Network architecture along with Ensemble Voting classifiers were used for training. 5-fold cross validation is applied to generalise the model. The study exhibited the highest accuracy of 94%.

C. GAIT Analysis

[9] proposed the work on the basis of PhysioNet repository's Vertical Ground Force Reaction(VGFR) dataset which had features from uncoordinated walk observed in PD affected Patients. It also integrated the voice-based classification for a hybrid model. SVM, XGBoost and MLP algorithms were implemented which resulted in an average accuracy of 88.17%.

In [10], hyper-parameter optimisation is achieved using a Sequential Bayesian Model-based Optimization(SBMO) methodology implemented using the Tree-structured Parzen Estimator(TPE) algorithm. Binary and multinominal classifications are performed using very deep neural networks. A validation accuracy of 0.991 is obtained and is proved to be considerably more than the other models trained on similar dataset.

In [13], Gait Daphnet Freezing dataset is considered for 10 subjects. To select essential features, a wrapper method is used and the Boruta algorithm is implemented. tDistributed Stochastic Neighbour Embedding (t-SNE) along with Principal

Component Analysis (PCA) is used in exploratory analysis. Among the considerable GAIT features, FoG, Walk and transition characteristics are scrutinised. It was observed that the Support Vector Machine with polynomial kernel function (SVMP) model resulted in the highest accuracy of 89%.

D. Neuroimaging

In [11], The CNN models are fed MRI slices of 3D brain scans. Three different Convolutional Neural Network(CNN) architectures are used to compare and extract essential features from the images. VGG16, VGG19 and InceptionV3 are the models used for transfer learning. Among these, VGG19 performed the best with an accuracy of 91.5% compared to 88.5% for VGG16 and 89.5% for InceptionV3.

[12] proposes a deep convolution neural network classifier that employs transfer learning and Generative Adversarial Networks (GAN)-based data augmentation techniques. PSNR value is quite high which indicates that the image is much clearer with less distortion. The already trained AlexNet architecture is used for the new image dataset and results in 89.23% accuracy.

In [15], deep learning techniques to processes NIFTI images and create 3D convolutional neural network for brain tumor segmentation is presented. Deep convolutional neural networks based on depth and spatial exploitation can further be explored for Parkinson's disease detection.

III. Approach

A. Dataset

The dataset used in this project consists of functional Magnetic Resonance Imaging(fMRI) image scans. Considered to contain sensitive clinical information, the data requires permission through a consent form to be accessed.

The Parkinson's Progression Markers Initiative(PPMI) is a platform based on empirical clinical research to extensively analyse biological specimen, complex imaging and physiological assessments to recognize vital biomarkers in the progression of Parkinson's disease. The data collected from research contributors has assisted in the establishment of a substantial biorepository, which can now be accessed by researchers worldwide to carry out advanced studies.

The PPMI dataset included 3D MRI scans in DICOM and NIfTI file format. DICOM is a streamlined format for transferring and relaying medical images, allowing the integration of imaging systems from various manufacturers. NIfTI is a new examinable data format that privileges advanced analytical services for functional MRI scans. Data of the NIfTI file format of 15 PD and 13 control patients with no age limitations was retrieved from the Parkinson's directory for this research project.

B. Data preprocessing

We use Python's package Nibabel to examine and investigate NIfTI files. It permits the loading and interpretation of NIfTI images and allows their conversion to NumPy arrays in a precise method. Nilearn is a module in Python that facilitates speedy and effortless statistical analysis on NeuroImaging data by leveraging the scikit-learn tools. We use Nilearn to plot our 2D slices and to study the voxel coordinates.

Chris Rorden developed MRIcro, an image analyzing application for clinical imaging. It enables medical images to be viewed on Linux and Windows Computer systems. It is a stand-alone framework that involves development tools for neuroimagers to interpret MRI, fMRI, and PET scans. MRIcro makes it simpler to view and share brain imagery. Furthermore, it enables researchers to highlight regions of interest or ROIs such as the Substantial Nigra in Parkinson. It can generate an examinable format header allowing conversion of brain imagery to other formats like DICOM, .png and .jpg. This seems to be beneficial for illustrating illness in brain regions with substantial damage as shown in Fig. 1.

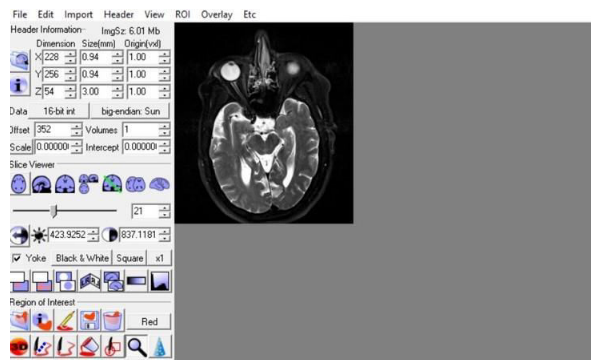

Fig. 1. MRIcro tool

We used MRIcro tool to segment the 3D .nii scans into 54 3mm slices as shown in Fig. 2. The slicing was done over the z-axis i.e. axial planes.

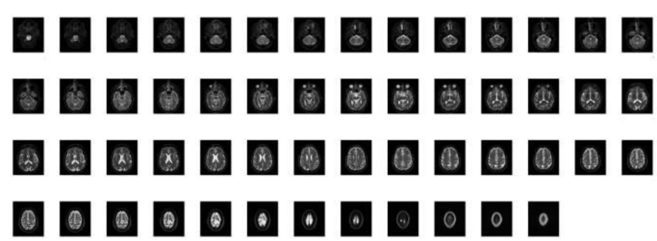

Fig. 2. 2D slices of a .nii image

[6] discussed about diabetic retinopathy from retinal pictures utilizing cooperation and information on state of the art sign dealing with and picture preparing. The Pre-Processing stage remedies the lopsided lighting in fundus pictures and furthermore kills the fight in the picture.

C. Classification models

A category of deep neural networks, often used for the analysis of visual images is the Convolutional neural network or CNN. These models are made up of diverse layers of artificial neurons. It employs an exceptional approach named Convolution. Here, a filter or a kernel which is represented by a matrix is applied to the input image and the 'convolved' features are extracted. Each layer also induces some activation functions that are passed on to the next layer along with the acquired features. As we progress through the layers, the features procured become more complex. The first layer generally defines primary features such as lines and edges. Such outcomes when forwarded to further layers, can detect more intricate features such as faces or numbers.

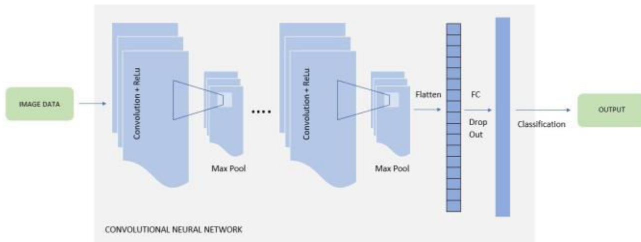

Fig. 3. CNN block diagram

[4] emphasized that Security is an important issue in current and next-generation networks. Blockchain will be an appropriate technology for securely sharing information in next-generation networks. Digital images are the prime medium attacked by cyber attackers. In this paper, a blockchain based security framework is proposed for sharing digital images in a multi user environment.

While designing the 2D-CNN model, the dimensions of input slices were 512x512. We have used six convolutional layers with filters ranging from 16 to 128, kernel size of 3x3 and max pooling of 2x2. We applied activation functions ReLu and sigmoid to assist the network in learning better. To further optimise the model, we employed data augmentation technique for our dataset and batch normalisation in the convolution layers along with adam optimiser during compilation. A dropout function of 0.5 was used to prevent overfitting.

VGG16 or Visual Geometry Group is a convolution neural net (CNN) architecture that won the 2014 ImageNet Large Scale Visual Recognition Challenge(ILSVR) competition. This is regarded as one of the finest visual model architectures today. One of the most distinctive characteristics of VGG16 is that rather than a vast number of hyperparameters, it emphasizes maintaining convolution layers of 3x3 filter with stride one and always having the very same padding. It issues a maximum pooling layer of 2x2 filter with stride two. Throughout the design, this configuration of convolution and max pool layers is uniform. Furthermore, it features two fully connected layers and a softmax activation function in output. The 16 in VGG16 signifies the concept that it comprises 16 weighted layers. This network is rather huge, with 130+ million (estimated) parameters. In our project, we have used transfer learning to leverage the use of VGG-16 for training and testing our data.

[8] discussed that Tumor segmentation required also the identical automatic initialization as regarding the liver. This phase was applied only in order to liver volume, obtained following automatic delineation of lean meats surface: this latter, used to original dataset quantity, was used as a new mask in order to be able to prevent processing overloads and even avoid errors related to be able to arsenic intoxication surrounding tissues delivering similar gray scale droit.

The key reason for LeNet-5 model's appeal was its basic and easy construction. It is an image categorization multi-layer convolution neural network. The network is dubbed Lenet-5 since it contains five layers with learnable parameters. It has two sets of convolution layers with max pooling combination. It offers two fully connected layers after the convolution and max pooling layers. Finally, a Softmax classifier classifies the photos into their corresponding classes. Apart from Softmax, we also induced ReLu activation function and batch normalization to optimise our model better.

IV. Inference

It was observed that the 2D-CNN, VGG16, ResNet50 and LeNet-5 models gave a training accuracy of 99.70%, 99.09%, 99.31%, and 99.62% respectively. The test accuracy has been represented in fig.4. The highest accuracy was observed by the novel 2D-CNN architecture designed and proposed for this system as an advanced deep learning model for Parkinson's disease detection. The optimisation was induced by constructing a six-layered CNN model along with batch normalisation, data augmentation and dropout methods.

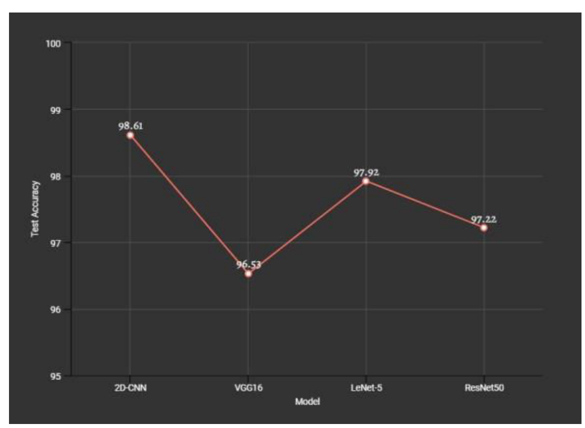

Fig. 4. Test accuracy of models

V. CONCLUSION

In this study, we used the CNN deep learning architecture with data augmentation and the dropout technique for the classification of Parkinson's Disease patients from normal control ones with the highest testing accuracy of 99.70 percent. In comparison to other models presented in this field of research, this paper present a much higher accuracy and propose a novel model architecture based on CNN. This model was trained using a colossal amount of data. Parkinson's disease progression may also be predicted using this method, as well as Parkinson-related cognitive deterioration. We tried to minimise overfitting by making changes to the size of kernels, the number of layers, and the number of neurons for respective layers of the model. Data augmentation and dropout processes were also used to develop an exceptionally efficient system.

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