PARKINSON'S DISEASE DETECTION USING FMRI IMAGES LEVERAGING TRANSFER LEARNING ON CONVOLUTIONAL NEURAL NETWORK

ASADUZZAMAN SAJEEB, A.F.M. NAZMUS SAKIB, SANJIDA ALI SHUSHMITA, S. M. ASHRAF KABIR,
MD TANZIM REZA, MOHAMMAD ZAVID PARVEZ

Software Engineering and HCI Research Group, Department of Computer Science and Engineering,
Brac University, Bangladesh

E-MAIL: {sajeebasaduzzaman, nazsakib16, sahanaali1979, ashrafkabir95, rezatanzim}@gmail.com,
zavid.parvez@bracu.ac.bd

Abstract:

Parkinson's disease(PD) is a neurological condition that is dynamic and steadily influences the movement of the human body. PD influences the central apprehensive system which happens because of the hardship of dopaminergic neurons brought about in a neuro-degenerative incubation. The patients who have PD usually suffer from tremor, unyielding nature, postural shifts, and lessen in unconstrained advancements. There is no particular diagnosis process for PD. PD varies from one person to another person depending on the situation and the family history.Magnetic Resonance Imaging (MRI), Computed Tomography (CT), ultrasound of the brain, Positron Emission Tomography (PET) scans are common imaging tests to figure out this disease but these tests are not particularly effective. In this research, several tests are run on two types of data group - control and PD affected people. The dataset is collected from the Parkinson's Progression Markers Initiative (PPMI) repository. Then MRI slices are processed from the selected data group into the CNN models. Three different Convolutional Neural Network (CNN) architectures are used in this work to extract features from the data group. The CNN models are InceptionV3, VGG16 and VGG19. These models are used in this research to compare and to get better accuracy. Among these models, VGG19 worked best in the dataset because the accuracy for VGG19 is 91.5% where VGG16 gives 88.5% and inceptionV3 gives 89.5% accuracy on detecting PD.

Keywords:

Parkinson's Disease (PD), neurological condition, dopaminergic neurons, PPMI, MRI, CNN,PET, extract features, InceptionV3, VGG16, VGG19, accuracy.

1. Introduction

Parkinson's Disease(PD) is a dynamic neuro-degenerative disease which causes several motor and non-motor effects on the subject that carries the disease[1]. This is a dangerous disorder continuously affects the patient in a bad way over time [2]. Those who have adult onset PD are usually above the age of 60 but early onset PD and juvenile PD also exist. According to the PD establishment, although the PD affected people of the age under 50 is only 4%, the predominance of PD increases with the increasing age. [2] About 60,000 patients within the U.S. are analyzed with PD every year [2]. Around the world, 7 to 10 million individuals are suffering from this disease. Those people who have a family history of this disease are a little more exposed at the chance of being effected by PD. Presently, there are no well-known treatments for this disease, but drugs and surgeries are a few remedial choices to diminish the side impacts for Parkinson's disease [10].
Longer life expectancy and the prevalence of older and debilitated population [3] - [8] encourage us to create techniques to decrease healthcare prices. There are various investigations works are going on Parkinson's Disease (PD) which appeared to be the second most common malady within the world and it is still expanding until this day.

This paper aims to detect Parkinson's Disease using data from Function Magnetic Resonance Imaging(fMRI) images to differentiate PD affected people. The contribution of the paper is (1) it proposes a method to identify PD with nearly 90% accuracy which as almost as good as human level accuracy and (2) it serves as a comparison between the performance of all the popular deep learning architectures.

The rest of this paper is organizes as follows. The chapter

II describes the background study,chapter III is about data description,chapter IV talks about the proposed model of this research,chapter V presents the result and analysis part and the conclusion of this research is in chapter VI.

2. Background Study

2.1. Previous Works

Patel, Lorincz, et al. [11] used Support Vector Machine (SVM) classifier in order to estimate dyskinesia, bradykinesia and tremor on their research where accelerometer's data was used. Trained clinicians performed the analysis of the recordings of the video where they made assessment of PD symptoms and motor complications. Authors generated results in time series format and after that they compared it to clinical scores estimation from the data of accelerometer by using different kernels of SVM.

In paper [12] authors developed a system named MercuryLive which is a platform for monitoring home of PD patients and it uses sensors which are wearable. In order to measure clinical scores of the severity of tremor, dyskinesia and bradykinesia, the system was able to analyze the data from sensor. From their results, data latency was below 400ms and the video latency was 200ms alongside 13 frame per second on video. Moreover, the bandwidth was 800 kbps and video compression rate were 40%. Their system was able to monitor only the patients of PD whom were at the last stage of the disease.

Brewer, Pradhan et al. [13] created a protocol named Advanced Sensing for Assessment of Parkinson's disease (ASAP) by using data from various sensors. Authors used this ASAP protocol to assess the motor disability of early and moderate PD which were reliable and quantitative. Modified regression techniques were used in this protocol and 26 individual's data were summarized into 36 variables. Besides, authors found approximately 3.5% prediction error and 76% of the variability of UPDRS were calculated. Finally, authors stated that, their ASAP protocol can figure out the changes in the motor signs of individuals.

In paper [14], authors described an internet of things (IoT) platform which works with real-time data from PD patients. Their system collects data from PD patients using wearable sensors which can be installed into patient's clothes and connected to medical database through internet using via mobile phone or tablets. After data collection, different algorithms can be used to analyze the condition of the PD patients such as – physical conditions, medications, progression of the disease, etc.

Although there are lots of work such as the mentioned above, there is not really much work related to the comparison of the performance of the popular deep learning models, something that we have addressed with our proposed work.

2.2. Models

VGGNet accomplishes 92.7% test exactness on ImageNet dataset which contains 14 million pictures having a place with 1000 classes. This system is portrayed by methods for its simplicity, the utilization of just 33 convolutional layers stacked on each other in developing depth[17]. VGG19 and VGG16 both have been used in this research.
An Inception network is a system such as modules with incidental max-pooling layers with stride 2 to split the choice of the grid [18]. This network obtained lower error rate with 42 layers deep and it is significantly more productive than VGGNet [19].

Till nowadays, in many hospitals, these pictures are deciphered manually by doctors; with included plausibility of human made mistake. Considering, PD can be detected with manually with 80.6% medical exactness[15], latest innovations like Artificial Neural Network (ANN) may do better in terms of classifying PD. If accurate enough, these Artificial Intelligence (AI) based models may perform better than human being.

3 Dataset Description

The fMRI dataset is collected from the Parkinson's Progression Markers Initiative (PPMI). PPMI usually work on Parkinson's Disease and its prevention. PPMI provides clinical, imaging and biomaker data to the PD researchers. Those are raw data and in Magnetic Resonance Imaging (MRI) and Single-photon emission computed tomography (SPECT) images format[16].

In order to access the data in faster and efficient way, data preprocessing is necessary. The dataset contains a total of 604 people's fMRI data. The fMRI data came in 3D volumes and we extracted the 2D slice from it. The detailed dataset description is presented in table 1 and different graphs are represented below table 1.

TABLE 1. Data formats of fMRI.

Data Format	Count of Data Format
DCM	16
NII	587

A nii nifti-1 data format is a special file format by Neuroimaging Informatics Technology Initiative which is one type of fMRI data format. Data are stored in voxels of different time series where there are millions of voxels.

TABLE 2. Different groups of PD from dataset.

Group	Count of Group
Control	20
GenCohort PD	17
GenCohort Unaff	30
PD	221
Phantom	258
Prodomal	44
SWEDD	13

There are 7 different groups in the dataset which is given in table 2. Most patient are in Phantom group which are the victim olfactory hallucination, a pre-condition for PD. This group's people often smell an odor that is not actually there. This smell can be of burned, foul, spoiled, or rotten smell. The other group is PD which means those people who are this group are already affected in PD.

TABLE 3. Gender of patients of dataset.

Sex	Count
Male	131
Female	258
Unknown	214

There were male, female and x indicates the unknown gender in the dataset given in table 3.

There are two states in the fMRI data. They are resting state and BOLD state given in table 4.
Experiment studies many subjects where the subject is usually PD affected and non-affected person. Each subject may be scanned during multiple sessions. Each session consists a several runs. Each run consists of a series of brain volumes. Each volume is made up of multiple slices. Each slice contains many voxels. Each voxel has an intensity associate with it. In a 64*64 matrix there is 192/64=3mm voxel.

TABLE 4. Different states of patients of dataset.

Description	Count of Description
ep2d_bold_rest	52
ep2d_RESTING_STATE	551

4 Proposed Model

The proposed model evolves around processing the dataset and training the model with it.

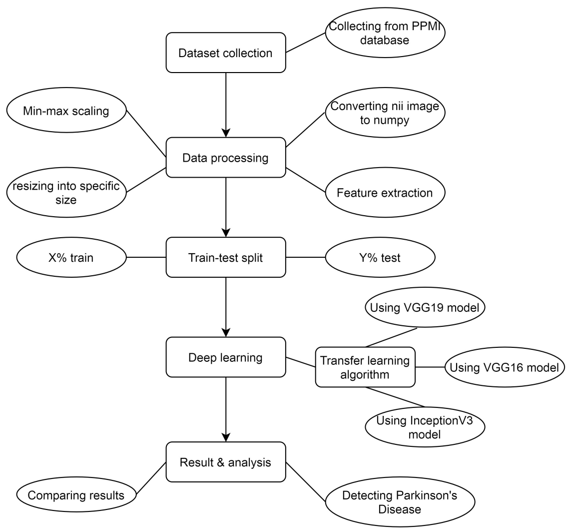

FIGURE 1. Structure of proposed model.

The whole workflow of this proposed model can be easier to understand from figure 1 where each step is shown sequentially to visualize the structure of our model quickly and easily.

4.1. Dataset Collection

the dataset has been collected from the Parkinson's Progression Markers Initiative (PPMI) database.PPMI usually work on Parkinson's Disease and its prevention.Moreover PPMI provides clinical, imaging and biomaker data to the PD researchers.

4.2. Data Processing

After separating Parkinson's disease affected people and non-affected peoples from the dataset, the 3D images have been converted into 2D images. Then the nii format images have been converted to NumPy. Then min-max scaling has been applied to normalize the data into a specific size and feature extraction has held in.

4.3. Train-test Split

In this section the data has been split into the train-test category where 60% data have been kept to train and 40% for the test.800 MRI slices have been passed to the different CNN architectures for training the prediction model and around 550 slices were utilized to test the accuracy.

4.4. Deep Learning

On this step, Deep Learning was applied while leveraging the Transfer Learning technique for Image Classification. The Transfer Learning is mainly used to achieve faster convergence of the CNN models and to achieve higher accuracy. Three different architectures of the CNN model are used on the dataset which are VGG19, VGG16, and InceptionV3.The prediction model is obtained in which the subjects are tested for acquiring the desired result that whether the patient has PD or in the control stage. The Deep Learning (DL) models that simple linear or non-linear equations are used to attach the outputs among layers. They make use of low-level functions to transform into higher-level abstract features. They maintain track of the increasingly abstract representations of the input data and have the capability to frequently learn about those factors. DL worked distinctly better when it comes to solving complicated problems, like image classification of our dataset. It makes use of a huge quantity of parameters which is needed most for this proposed model. The softmax classifier is implemented upon the deep CNN methods to derive the classification output in the dataset.

4.5. Result and Analysis

Finally, the efficiency of Parkinson's Disease detection is measured by comparing and analyzing the results. We have mainly checked the accuracy of the three CNN architectures and compared between them in graphical representation.

5 Result and analysis

This section describes the accuracy and comparison between accuracy from different models. The accuracy has been calculated by using an epoch of 1, 5, 8, 10, 15, 18 and 20. Within 20 epoch almost ninety percent accuracy has been achieved.

5.1 Result for VGG19

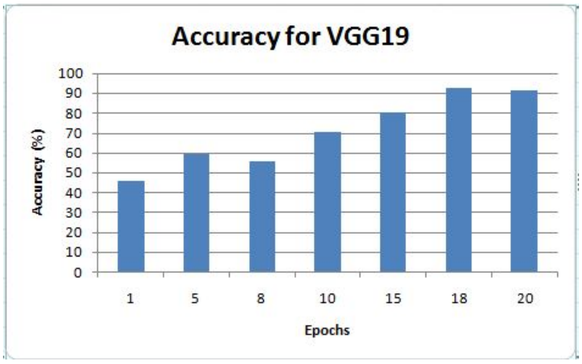

FIGURE 2. Bar graph of accuracy for VGG19.

In figure 2, the accuracy of detecting Parkinson's disease has been found when employing a convolutional neural network's architecture VGG19. 20 epochs has been run in VGG19. An accuracy for each epoch has been acquired. Whereas running the 1st epoch 45.5% accuracy has been achieved. At the 10th epoch it expanded to 70.5%. Essentially on the encourage ages the accuracy expanded. The most elevated accuracy has been obtained at 20th epoch which is 91.5% utilizing VGG19.

5.2 Result for VGG16

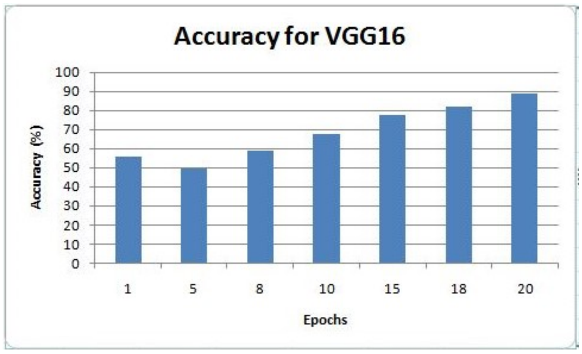

FIGURE 3. Bar graph of accuracy for VGG16.

Within the figure 3, the accuracy of detecting a Parkinson's disease has been found when employing a convolutional neural network's architecture VGG16. Essentially, 20 epochs have been run in VGG16 as well. Whereas running the 1st epoch the accuracy for detecting Parkinson's disease was 55.5%. While running the 10th epoch the accuracy has been induced up to 67.5%. And the highest accuracy has been obtained whereas utilizing VGG16 was 88.5% which was within the 20th epoch.

5.3 Result for InceptionV3

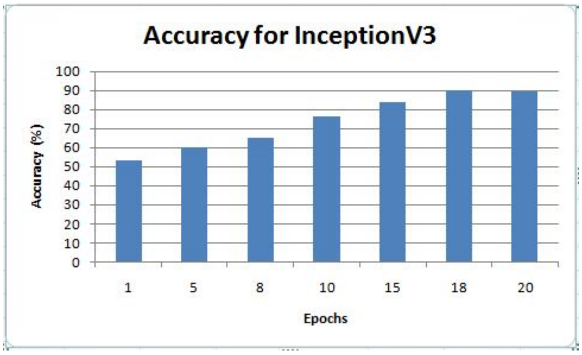

FIGURE 4. Bar graph of accuracy for InceptionV3.

Within the figure 4, the precision of detecting a Parkinson's disease has been found when employing a convolutional neural network's architecture InceptionV3. So 20 epochs have been run in InceptionV3 as well. Running the 1st epoch, the accuracy of 53.0% has been obtained for the location of Parkinson's disease. The accuracy drastically increased within the 10th epoch to 76.5%. After further running the epochs at the 20th epoch the most noteworthy accuracy of 89.5% has been obtained.

5.4 Comparison and discussion

In figure 5, the accuracy of different models has been shown. The highest accuracy between all the epochs has been taken and plotted for a better view. The graph shows that within the 1st epoch VGG16 gives 55.5% accuracy where VGG19 allows the accuracy of 45.5% and the InceptionV3 gives an accuracy of 53.0%. So, it can be said that VGG19 is the worst performing model in the case of the 1st epoch. In the 5th epoch, the most noteworthy accuracy from running the epoch for VGG19 is 70.5%, for VGG16 is 67.5% and for InceptionV3 we get 76.5%. Within the 10th epochs InceptionV3 has the most elevated accuracy of 76.5%. Besides, within the 15th

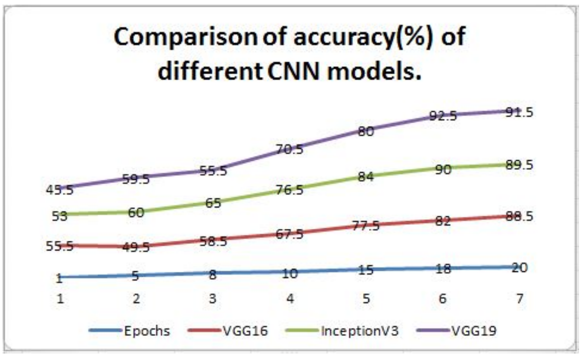

FIGURE 5. Comparison of accuracy of different CNN architectures.

epoch the highest accuracy we achieve was 80.0% for VGG19, 77.5% for VGG16, and 84.5% for InceptionV3. Here InceptionV3 has the most noteworthy accuracy. Within the 18th epochs it can be seen that the accuracy improves even further. Here, VGG19 gives the highest accuracy which is 92.5% where VGG16 gives 82% and for InceptionV3 it is 90%. Within 20 epochs for VGG19 model the highest accuracy is 91.5%, for VGG16 the most elevated accuracy is 88.5% and for InceptionV3 it is 89.5%.
Thus the final decision has been made that the classification accuracy of using the VGG19 model gives the best performance and accuracy in this research on detecting Parkinson's Disease.

6 Conclusion

This proposed prediction model is aimed to make it simpler for doctors to do exact determination and prediction of PD from the comparisons of different classifiers of patients who have been affected by PD based on their neuro-image. The work of detection and prediction strategies has been isolated to distinguish and measure the region of the brain that is affected because of PD, and use that information in a neural network to create the prediction model. In this paper, PD has been successfully detected with 91.5%, 88.5%, and 89.5% accuracy utilizing different CNN deep learning architectures which was trained and tested with a huge number of images. By comparing the results, it can be said that among these three models VGG19 works best in this dataset. This technique takes exceptionally less processing power and its accuracy is reliable. By creating a usable computer software with this approach can promptly help doctors to detect Parkinson's with better accuracy than ever before. However, more complex network architecture along with more convolutional neural layers is recommended for future works and more complex problems.

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