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Early Diagnosis of Parkinson's Disease in brain MRI using Deep Learning Algorithm

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Abstract—**The Parkinson's disease (PD) is one of the top most prevalent degenerative disease which is caused by the loss of neurons that produce dopamine. Magnetic Resonance Imaging (MRI) is capable of capturing changes in the structure of the brain caused due to deficiency of dopamine in subjects of Parkinson's disease. Early diagnosis of these type of diseases using computer-aided systems is an area of eminent importance and extensive research amongst researchers. Deep learning models can effectively assist the clinicians in the PD diagnosis and obtain an objective patient group classification in coming years. In this paper, detection of PD is done using deep learning algorithm to discriminate between PD and controlled subjects, which is difficult and time taking if done manually. According to research, the chance of curing increases significantly if appropriate steps are taken early and precious time could be saved if detection process is carried by a computer. By making use of the Convolutional Neural Network (CNN) and the LeNet-5 architecture, the MRI data of PD subjects was successfully classified from normal controls.**

Keywords— LeNet-5, Parkinson's disease, Python, Deep Learning, Keras, CNN

I. INTRODUCTION

Parkinson's disease (PD) is a disorder of the central nervous system which has an effect on movement, many times including tremors. It demonstrates as the death of neurons creating dopamine in the midbrain [5]. It has a range of symptoms such as vocal changes, tremors, muscle rigidity, postural instability and slowed movements. Non-motor symptoms comprise of sleep behavior disorders, depression, cognitive impairment and loss of sense of smell. As PD is chronic and slow-developing, the symptoms may worsen over time. The main cause of PD is unknown; however, it is researched that environmental factors along with genetic factors play a big part in causing PD. It targets elderly people, mostly above the age of 60 years. The disorder was described as "shaking palsy" the earliest by James Parkinson [6]. Detecting PD accurately at early stages is certainly vital in delaying the progress and offering patients some possibility of access to good therapy. Diagnosis of neurodegenerative diseases has been improved considerably by using 3D magnetic resonance imaging (3D-MRI). Main intention behind implementing the classification on clinical medical data is to possibly come up with a predictive model in order to recognize and classify subjects affected from PD and controlled subjects or to reckon the disease's stage. In preceding years, deep learning algorithms have accomplished striking performances in numerous fields that include computer vision, NLP (natural language processing) and speech recognition. Many changes are being brought about by deep learning in other fields like engineering and biology [7]. Studies propose deep learning frameworks for the diagnosis of various diseases in their early stages. Diagnosis of any disease is divided into two key stages: the training stage and the testing stage. A research paper [1] briefly discusses the current deep learning architectures that are used for MRI and medical image for image classification, segmentation, detection, etc. It largely focuses on the application of deep learning in disease diagnosis that makes use of MRI modality along with various challenges and recent developments in deep learning related to the analysis of these images. Over the years, to solve critical image classification problems, researchers and students have analysed and worked on artificial neural networks. In recent times, a deep learning technique, CNN or convolutional neural networks, has shown splendid results in image classification for analysing image content. One of the advantages associated with the above-mentioned neural networks is the fact that we can generalize them to obtain optimum solutions to distinct problems making use of the same consistent design. The paper [1] illustrates an in-depth literature review of deep learning techniques. At present, Neural networks have been gradually used at a surprising rate. Deep neural networks are largely used in different areas of machine learning models from image analysis to natural language processing (NLP) and are broadly conveyed in scholarly industry. Another remarkable research [2] highlights the provocations of feature selection and reduction one faces while performing image classification. It describes problems in selection of majority of the discriminative and precise features that are essential for classification model building. It propounds that shift and scale invariant features extracted using convolution neural network along with a subsequent deep learning classification constitutes the best effective way of differentiating disease affected data from control data in functional MRI (fMRI). In paper [2], a CNN architecture

has been implemented which efficiently classifies fMRI data of Alzheimer's subjects from controlled subjects [2]. Another piece of research [3] proposes a strong deep learning system to recognize the stages of progression in AD patients on the basis of PET and MRI scans. Dropout technique is employed to better the traditional deep learning approach by deterring weight coadaptation, which proves to be one of the causes of overfitting. Additionally, stability selection, which is a multitask learning strategy and an adaptive learning factor, is also incorporated. This proposed method was conducted for MCI and AD conversion diagnosis. Another paper of relevance [4] proposes a technique of extracting brain tumour from 2D-MRI by Fuzzy C-Means clustering algorithm prior to traditional classifiers and CNN. It depicts how the neuroanatomical biomarkers obtained through MRI were studied by the researchers and they were able to conclude that the MRI scans are useful in detecting or diagnosing PD. In this paper, six traditional classifiers such as Naive Bayes, Random Forest, Support Vector Machine (SVM), Multilayer Perceptron (MLP), K-Nearest Neighbour (KNN), and Logistic Regression are implemented in scikit-learn to assess their ability to differentiate between abnormal and normal pixels on the basis of statistical-based and texture-based features. This notion of using the MRI scans and Convolution neural network motivated our algorithm to use a CNN architecture LeNet-5, once with and then without the batch normalization technique, over a subset of variables, to come up with an effective model for image classification. Even so, the most efficient model is the one in which both batch normalization and dropout algorithm are used.

II. DATA AND METHOD

The dataset was obtained from Parkinson's Progression Markers Initiative (PPMI). PPMI is a landmark observational clinical study to fully evaluate groups of noteworthy interest using behavioral and clinical assessments to recognize biomarkers of progress of PD. In neuroimaging, biomarkers refer to the measures obtained from images which depict the presence or absence of a disease or its severity, which is useful for early diagnosis. The protocol contained T1-weighted (T1w) MRI images based on a scanner by Siemens. The 3D MRI dataset was in DICOM format and NIFTI format. We extracted the data in the DICOM format from the Parkinson's database and biorepository for this study. The DICOM format is known to transmit and exchange medical images in a standardized format, allowing the incorporation of the images from numerous manufacturers. The preprocessing of the images was done using the MRIcro tool. For this work, 30 PD subjects and 24 elderly controlled subjects (with ages from 60 to 75 years) were picked from the mentioned dataset. All PD affected subjects and controlled subjects were fit and healthy, and had reported negative history of neurological or medical conditions.

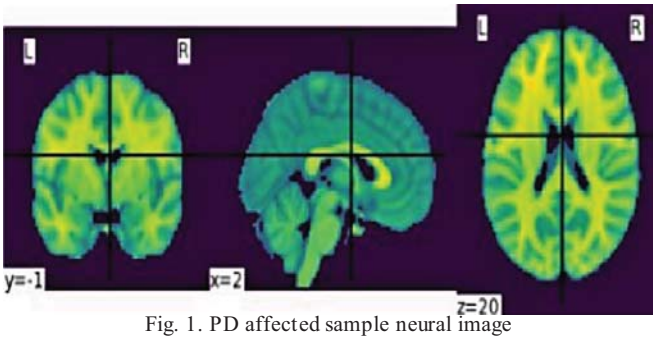


Fig. 1. PD affected sample neural image

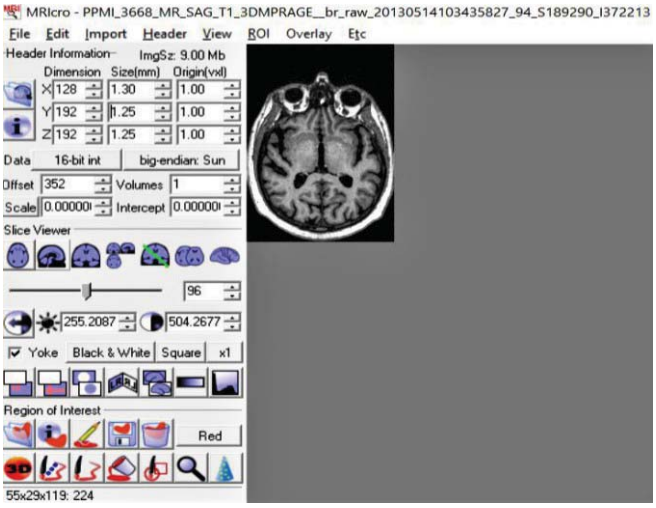


Fig. 2. Visualization of the PD affected MRI image in MRIcro tool

Afterwards, the images were labelled for the classification of PD vs control data so they could be used as input for deep learning, post which they were aligned to the respective high-resolution T1w scans. At the end, the last few slices of each image were discarded as they didn't contain any functional information. Finally, the useful images were 6,132 and 4416 for PD subjects and healthy/controlled subjects respectively. After preprocessing the dataset, TensorFlow was used in order to read the images. We labelled the images of PD subjects' MRI as '0' and images of controlled subjects as '1'. The dataset containing useful images was then divided into training and testing data, 90% of the images was for training and the remaining 10% for testing (9,493 images and 1,055 images respectively).

III. IMPLEMENTATION

We then performed One Hot Encoding, where an integer encoded variable is withdrawn for a new binary variable to be added for every distinctive integer value. The class vectors (integers) or categorical variables are converted into a binary class matrix for it to make a better prediction. The shape of the input dataset was 64*64*3. We used three Conv2D layers with number of neurons being 64, 32 and 16 respectively. 3*3 was the kernel size for all the three convolution layers. Activation function called rectified linear unit (or ReLu) was applied in all Conv2D layers. Each Conv2D layer was followed by a MaxPooling2D layer with a kernel size 2*2. 3D matrix obtained from these layers was converted into a 1D vector matrix by a flatten layer. Our baseline model consisted of two dense layers. The first one consisted of 128 neurons and ReLu activation function. The second and final fully connected/dense layer had two

neurons each and an activation function called 'Sigmoid'. We chose a batch size of 32 and the 30 no. of epochs. The model was trained and tested on the dataset for every epoch. Here, we observed that post applying the drop-out algorithm, there was an increase in the performance of the model. This algorithm is implemented to reduce overfitting and improve the accuracy of the model. Our purpose was to classify PD images from Control images. Therefore, LeNet-5 architecture was selected and adjusted for our dataset. LeNet-5 is a kind of CNN architecture wherein two Conv2D layers were used. Basic architecture of LeNet-5 is shown in Fig. 3.

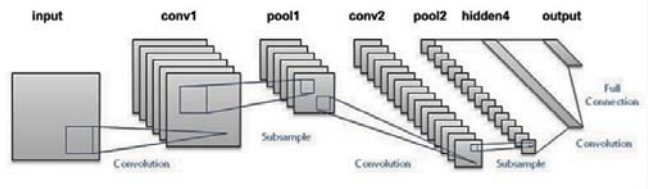


Fig. 3. LeNet-5 architecture

The first layer consisted of 32 neurons and the second layer consisted of 64 neurons with a kernel size 3*3. A ReLu activation function was used for both convolution layers. Then each Conv2D layer was followed by a MaxPooling2D layer, for which the kernel size was 2*2. Then followed one dropout and one flatten layer. Our LeNet-5 model had two dense layers, first having 128 neurons and a ReLu activation function, and the other one having 2 neurons and a consequent 'sigmoid' activation function. Post implementation, a model accuracy of 96.99% was achieved. We implemented the model again, this time with batch normalization. It allowed our network's every layer to learn by itself better with more independency. As a result, overfitting was reduced and the performance of the model improved. We made use of the 'Adam' optimizer for both models, which is an extension to the stochastic gradient descent procedure. Due to its bias-correction feature, it is recommended for binary classification problems. Since binary classification had to be done, the loss was specified as 'Binary Cross-Entropy', which is cross-entropy loss plus sigmoid activation function. Along with accuracy, loss function was also viewed to give a degree of error. A neural network tries reducing the error each time it fits a model, rather than attempting to increase the model accuracy.

IV. RESULT

In the LeNet-5 model, when no batch normalisation was performed, training accuracy and test accuracy were 96.65% and 97.62% respectively. The model loss was 0.07%. Fig. 3 is the plot for accuracy of the model.

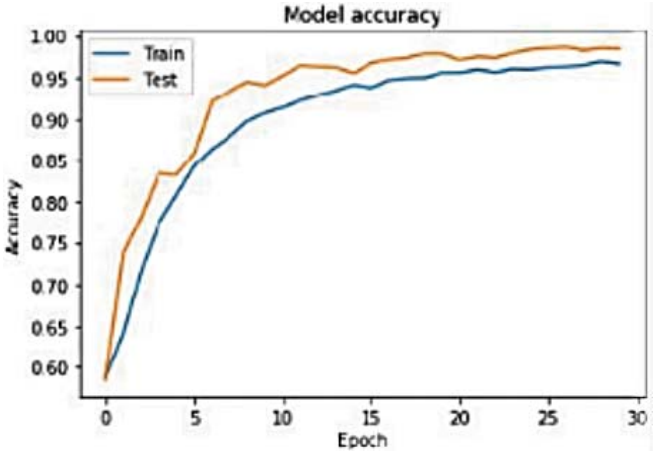


Fig. 3. Model accuracy of train and test dataset without batch normalisation

Loss function was used to measure how accurately the network identified the PD subjects. The plot depicting model loss is given in Fig. 4.

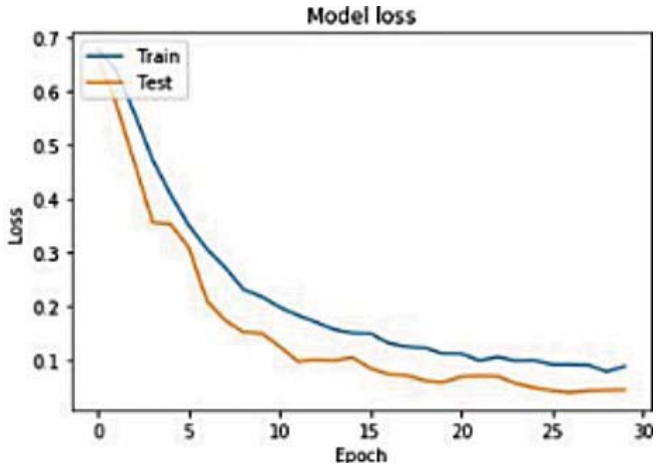


Fig. 4. Model loss of train and test dataset without batch normalisation

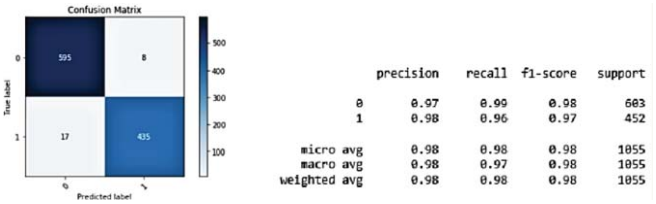


Fig. 5. Confusion matrix of model without batch normalization

The model in which batch normalization was performed, the training accuracy and test accuracy were 95.44% and 97.92% respectively. The loss was 0.05%. Plots depicting model accuracy and model loss are given in Fig. 6. and Fig. 7.

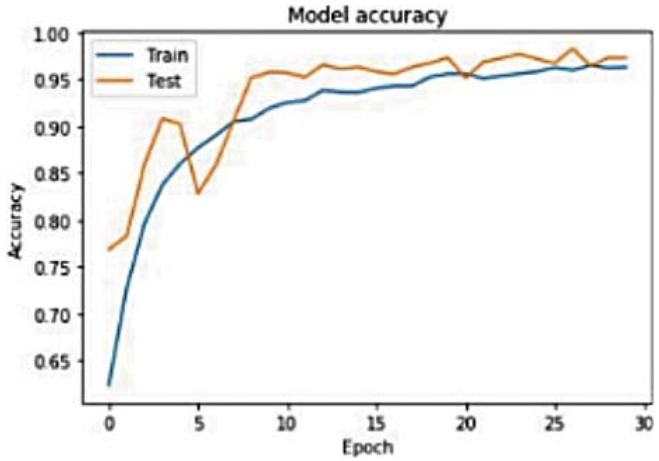


Fig. 6. Model accuracy of train and test dataset with batch normalization

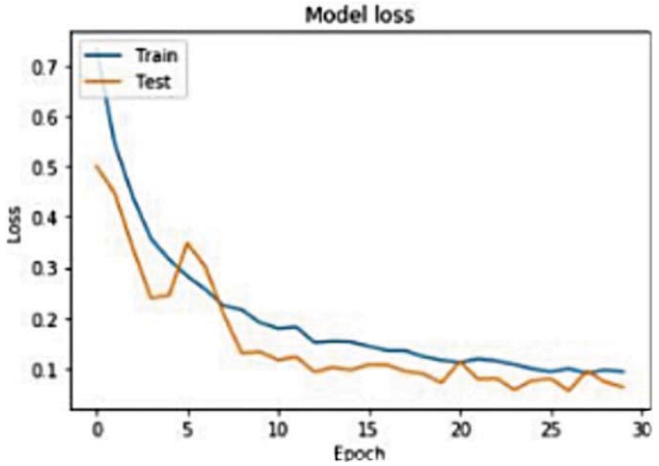
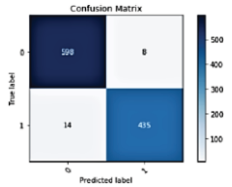


Fig. 7. Model loss of train and test dataset with batch normalization



	precision	recall	f1-score	support
0	0.98	0.99	0.98	606
1	0.98	0.97	0.98	449
micro avg	0.98	0.98	0.98	1055
macro avg	0.98	0.98	0.98	1055
weighted avg	0.98	0.98	0.98	1055

Fig. 8. Confusion matrix of model with batch normalization

V. CONCLUSION

In this paper, the diagnosis of Parkinson's Disease data was successfully performed, with and without batch normalization. 97.92% accuracy was achieved using LeNet-5 architecture with batch normalization technique and dropout algorithm. The model was trained using a big dataset containing 10,548 images. Implementation of this particular method for the purpose of diagnosing different stages of PD is viable. The accuracy of the model in which we did not apply batch normalization technique was 97.63%. Ways of optimising this model, to reduce overfitting and bias, are by changing the number of neurons in each layer, changing the kernel size, changing the no. of layers and using dropout algorithm. This research may open a future scope for analysing medical or neuro images, and allow physicians and researchers to perform feature extraction, selection and classification to potentially predict any new data.

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