CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632599
http://magellanes.com/

PARKINSON'S DISEASE ANALYSIS USING DEEP LEARNING AND VGG-16 MODEL-BASED APPROACHES

Archana Panda[1*], Prachet Bhuyan[2], Debasish Panda[3]

[1*,2,3]KIIT Deemed to be University, Bhubaneswar, Odisha, India, Email: 2081011@kiit.ac.in
Email: pbguyanfcs@kiit.ac.in, Email: devesure@gmail.com

Abstract
Parkinson's disease (PD) is an intricate neurodegenerative condition that impacts areas like the Substantia Nigra (SN), Red Nucleus (RN), and locus coeruleus (LC). Analyzing MRI data from PD patients necessitates anatomical structural landmarks for spatial standardization and structural partitioning. Machine Learning techniques and algorithms are crucial in identifying patterns in biological sciences. These strategies have been aiding researchers in categorising medical images and forecasting models to gain a thorough comprehension of intricate medical issues. Deep learning is an area of machine learning that focuses on Artificial Neural Networks (ANNs), which are algorithms designed to mimic the structure and function of the brain. This article utilises a VGG16 model to classify MRI brain images and distinguish between brains affected by PD with normal healthy brains and non-PD with abnormal and unhealthy brains. They are classifying intricate clinical MRI data to identify disorders such as Parkinson's disease or determine the disease's stage with VGG16 Machine Learning Techniques. By employing Machine Learning Techniques, we effectively categorised individuals with Parkinson's disease from those without the condition, achieving an accuracy rate of 95.34% without implementing batch normalisation. Consequently, our research can efficiently employ the same structure to carry out different medical image classification tasks or more intricate systems.

Keywords: Machine Learning, Parkinson's disease, VGG16, MRI, Deep Learning.

1. Introduction
Parkinson's disease is a progressive neurological ailment that mostly impacts the motor system, resulting in a variety of symptoms connected to movement. Parkinson's disease, named after the British physician James Parkinson who initially documented the ailment in 1817, is distinguished by the progressive degeneration of neurons in the brain that produce dopamine. Dopamine, a neurotransmitter, is essential for coordinating precise and regulated motions. As the neurons deteriorate, patients with Parkinson's disease exhibit symptoms like tremors, rigidity, bradykinesia (slowed movements), and postural instability. The aetiology of Parkinson's disease is not fully understood, although it is believed that a mix of genetic and environmental variables play a role in its pathogenesis. In addition to affecting motor function, the condition can cause non-motor symptoms such as cognitive impairment, emotional issues, and sleep abnormalities. While a definitive cure for Parkinson's disease does not currently exist, a range of treatment modalities, including pharmacotherapy, physiotherapy, and, in certain instances, surgical procedures, are employed to mitigate symptoms and improve the overall well-being of individuals grappling with this complex ailment. Continuing research endeavours aim to enhance our comprehension of Parkinson's disease and create groundbreaking treatments that could perhaps decelerate or cease its advancement.

2. Related Works
Primary-stage Parkinson's disease can be erroneously identified as other syndromes. Parkinson's

CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632599
http://magellanes.com/

Disease (PD) is sometimes confused with many atypical Parkinsonian disorders, which are characterised by unusual symptoms. Shah et al. (2018), described a CNN model based on CAD presented for the automatic diagnosis of Parkinson's Disease (PD). The model is trained using T2-weighted Magnetic Resonance Imaging (MRI) data samples. The model is being compared to other machine learning models. The limitation of intricate forms of MRI data provides challenges in determining the suitable architecture of a CNN. Hutchinson and Raff (2000), explain the loss of dopaminergic neurons in the Substantia Nigra pars compacta, resulting in depigmentation, is a prominent characteristic of Parkinson's disease (PD). While this may be observed by neuropathological examination, it is challenging to recreate using neuroimaging techniques accurately. Sasaki et al. 2006, introduced a technique called "Neuromelanin-Sensitive MRI" (NMS-MRI), which uses a 3T T1 weighted high-resolution fast spin-echo sequence to visualise the SNc. In their study, Malek et al. (2015) utilised a dataset of 40 characteristics and employed Local Learning Based Feature Selection (LLBFS) to identify the 9 most effective features. These features were then used to categorise people with Parkinson's disease (PD) based on their UPDRS score, dividing them into four categories: Healthy, Early, Intermediate, and Advanced. Nilashi et al. (2016) proposed a novel hybrid intelligence system that combines an Adaptive Neuro-Fuzzy Inference System (ANFIS) and Support Vector Regression (SVR) to forecast the course of Parkinson's Disease (PD). Additionally, other efforts were made to develop a PD prediction system utilizing a Parallel feed-forward Neural Network Astrom et al. (2011). This system was then compared to a rule-based system to suggest a decision model. Noor et al. (2020) define Deep Learning approaches as enabling the creation of high-quality learning representations of MRI image data allowing for the incorporation of several levels of abstraction through the use of numerous layers of processing. Yamashita et al. (2018) and Korfiatis et al. (2017) conducted a study on the Convolutional Neural Network (CNN) architecture has demonstrated exceptional performance in medical image classification tasks, namely in tumour classification. Varrecchia et al. (2021), A gait parameter-based artificial neural network method for detecting the existence and severity of Parkinson's disease. Guo et al. (2022), explain an examination of the identification and evaluation of Parkinson's disease by the analysis of walking patterns.

3. Research Methodology

The study's data was gathered from the PPMI database available at www.ppmi-info.org/data. The PPMI database for neuroimages is a significant, global, and multicenter study focused on investigating the biomarkers associated with the course of Parkinson's Disease. The MRI scans used for the study were based on specific imaging in the figure. All the scans used in the study were acquired using a single type of scanner. The scans included in the study were from people over 60 years old. 5440 MRI scans were chosen from the initial visits of the patients. Among these patients, the scans mostly belonged to two research groups: Non-PD (NPD) and Parkinson’s Disease (PD), with 3200 scans allocated to the NPD group and 2240 scans to the PD group.

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632599
http://magellanes.com/

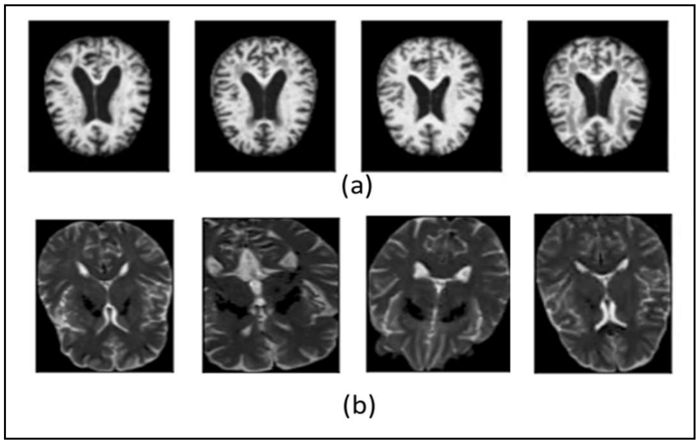

Figure 1: Sample MRI of Non-PD and PD

The above MRI scans from the Parkinson's Progression Markers Initiative (PPMI) database from both research groups: (a) MRI scan of a subject in the Non-PD group and (b) MRI scan of a subject in the PD group.

Proposed Model

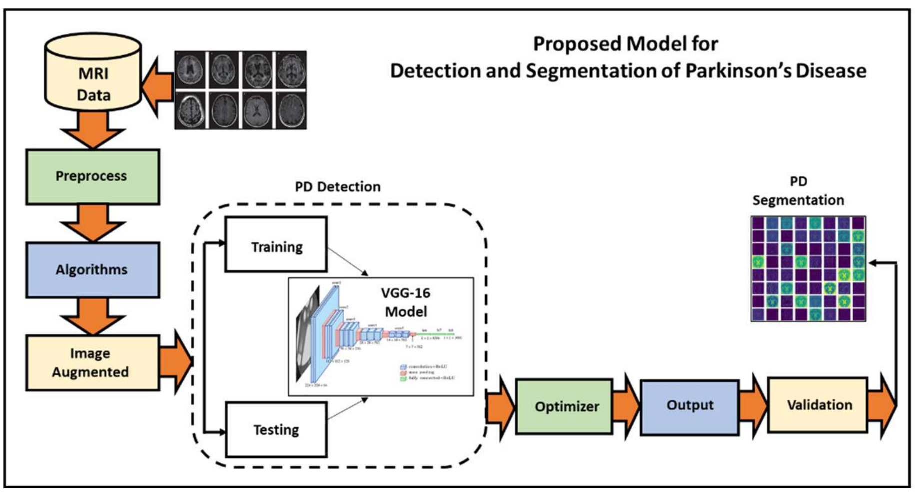

Figure 2: Proposed Model for Detection and Segmentation of Parkinson's Disease

The above-proposed model is designed to detect and segment Parkinson's Disease. In this model we used several steps first, the MRI data was collected from the PPMI database, and then we preprocessed the data to basic image operations where both the input and output are intensity images. Pre-processing aims to enhance important image features and reduce unwanted distortions in image data. After that, we used Keras a Python Neural Network API closely integrated with TensorFlow, used for constructing machine learning models. Keras models provide an uncomplicated and intuitive method to specify a Neural Network, which will subsequently be constructed using TensorFlow, after that we get the image augmented and transferred to the VGG-16 model then during the training of the deep learning optimisers model, adjust the weights for each epoch and reduce the loss function. An optimizer is a tool that modifies the parameters of a neural network, like weights and learning rates. Therefore, it aids in minimising the total loss and enhancing precision. Finally, the PD segmentation is done after the validation of the accuracy.

CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632599
http://magellanes.com/

4. VGG-16 Model

VGG-16 is a 16-layer Convolutional Neural Network (CNN) model. It is still regarded as one of the most superior and efficient models in existence today. The VGG-16 model design prioritises Conv Net layers with a 3×3 kernel size over multiple parameters. This model is significant since its values are accessible online and may be downloaded for integration into one's systems and applications. Compared to other established comprehensives, it is recognised for its simplicity. The minimum required input image size for this model is 224×224 pixels with three channels. Optimization methods in Neural Networks assess neuron activation by calculating the weighted total of inputs. Kernel functions are required to introduce nonlinearity into the output neuron. The neurons in a Neural Network work in conjunction with weight, bias, and the associated training process. The synaptic weights of the neurons are modified according to the level of error in the output. The input layer and activation function introduce nonlinearity to artificial neural input, enabling it to learn and perform intricate tasks.

VGG-16

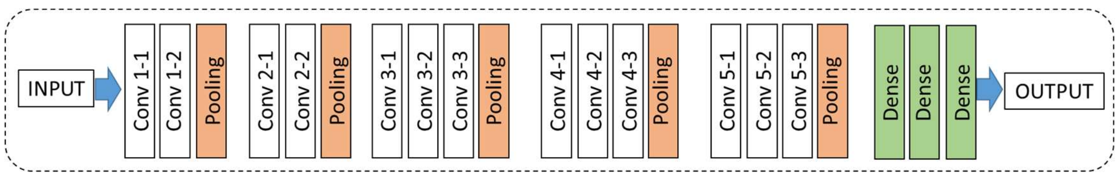

Figure 3: The typical VGG 16 network structure.

VGG16 is named after the 16 levels in the network that contain weights. VGG16 consists of 13 convolutional layers, 5 Max Pooling layers, and 3 Dense layers, totaling 21 levels. However, it contains only 16 weight layers, which are the learnable parameters. Additionally, it always incorporates a maxpool layer with a 2x2 filter and a stride of 2. The convolution and max pool layers are constantly positioned throughout the whole architecture. The Conv-1 Layer contains 64 filters, Conv-2 has 128 filters, Conv-3 has 256 filters, and Conv 4 and Conv 5 each have 512 filters. After a series of convolutional layers, three fully connected layers are used and the last layer is the soft-max layer.

5. Experimental Result

The MR images are trained using the suggested network model, utilizing the appropriate hyper-parameters as described in the preceding section. The initial convolution layer acquires the unprocessed input and carries out convolution on the images using the filters. The features collected at each convolution layer are seen as originating from pixels, edges from the pixels, shapes from the edges, and lastly complex areas as features from the shapes. These features are used to discriminate between the two classes. Figure 4 displays the feature of the trained crop images layer, which includes the initial 64 features. The network captures the properties of the variation in intensity levels and complicated regions, which are then used for the classification process. Therefore, the completely connected layers acquire the complex combination of attributes that were acquired by the preceding layers.

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632599
http://magellanes.com/

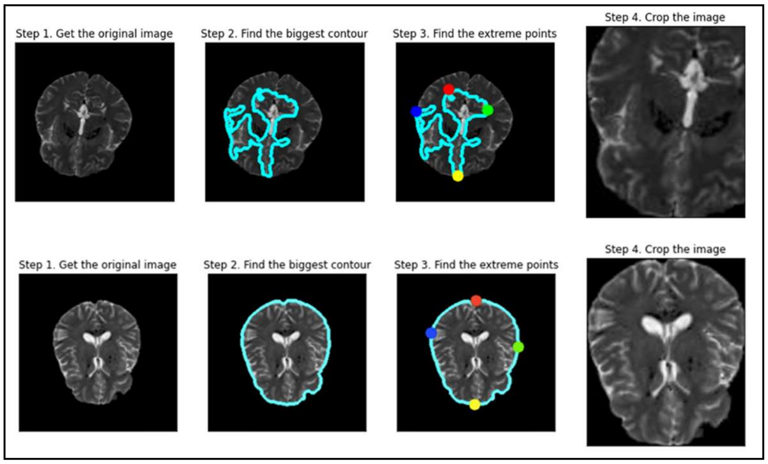

Figure 4: Trained the crop images

The above-trained images are split into 4 steps, step 1: get the original image, then in this image find the biggest contour in step 2 after that, find extreme points in step 3, and finally crop the image in step 4. The network undergoes 25 epochs of training, with each epoch being a complete iteration over the full dataset. The complete image dataset is trained and evaluated every 25 iterations to minimize the computational burden on the network and expedite the learning process.

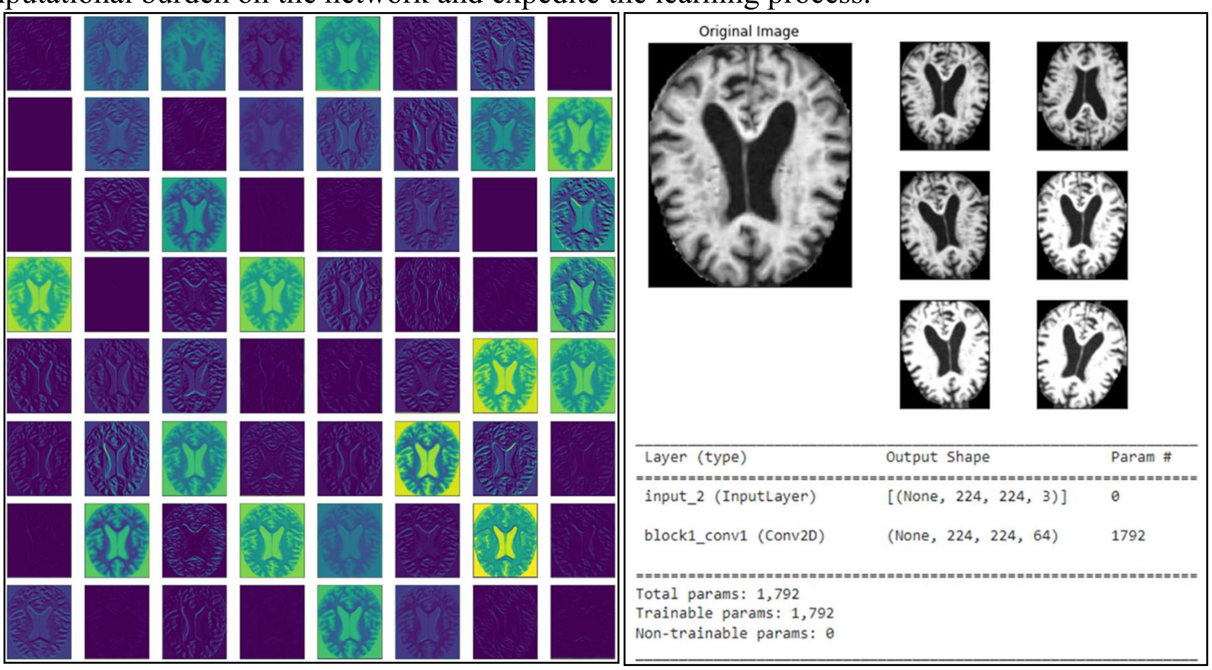

Figure 5: Augmented Image

The VGG-16 model is interpreted by visualizing the weights. The updated fully linked layer represents two classes: healthy control and Parkinson's illness. Finally displays the updated final completely connected layer for each class, namely Non-PD and PD. The final fully linked layer retrieves the discriminative features that can capture the structural variances between the two classes. The network's effectiveness for categorization is estimated by monitoring the accuracy and loss during both the training and test phases. The following Figure 6 displays the classification of Non-PD and PD images.

CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632599
http://magellanes.com/

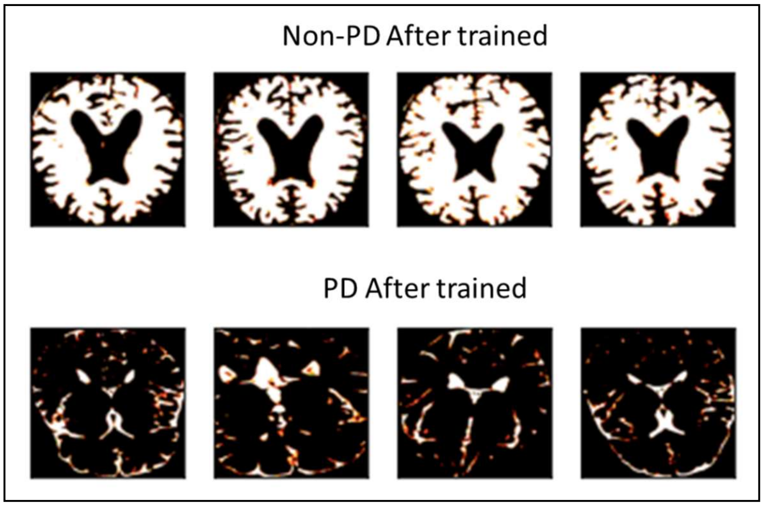

Figure 6: The classification of PD and Non-PD

The network's effectiveness for categorization is estimated by monitoring the accuracy and loss during both the training and test phases. The learning process reaches stability after 1796 cycles in both the training and testing phases. Figure 7 displays the loss that was experienced throughout both the training and testing phases. The loss or mistake rate in distinguishing between the Non-PD and PD images reaches a saturation point and remains constant after 1796 iterations, similar to the pattern observed in the learning curve. The suggested transfer learning VGG-16 architecture has a remarkable accuracy of 95.34%. This architecture demonstrates sensitivity and specificity scores of 90.80% and 89.40% respectively. The proposed approach can accurately classify MR images of people with PD and Non-PD without the need for complex image feature extraction and selection.

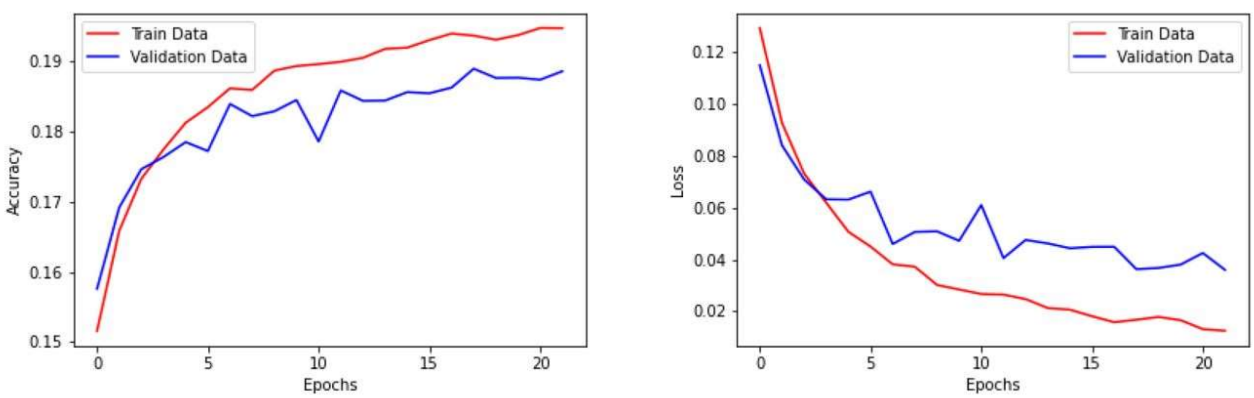

Figure 7: The accuracy and loss of the model with cross-validation

AUC/ROC, short for "Area under the ROC Curve," quantifies the performance of a classification model over different threshold values. It measures the degree to which the model accurately separates the classes and differentiates between them. In general, a higher AUC value indicates that the model accurately identifies the classes as they truly are. Our model's ability to differentiate between different stages of PD and classes improves as the AUC value increases. This graph displays the values of parameters such as True Positive (TP) and False Positive (FP) Rates.

CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632599
http://magellanes.com/

6. Conclusion

Parkinson's disease (PD) is a type of neurodegenerative disorder characterized by symptoms that become noticeable only as the disease advances. It is essential to choose the proper interventions, drugs, and neuro-rehabilitation treatments based on the specific stage of the disease and an individual basis. There are multiple issues with the conventional clinical assessment of Parkinson's disease in a clinical context. These factors encompass human mistakes and overlooked clinical observations, certain studies have suggested utilizing machine learning techniques on various datasets, to predict the severity of PD. This approach aims to differentiate between different stages of the disease and individuals who are healthy. The current study employed MRI data to classify phases of Parkinson's disease using deep neural networks and the VGG-16 Model. The findings of our study showed that the VGG-16 model we suggested achieved a prediction accuracy of 95% when using MRI data to differentiate between healthy individuals and those with Parkinson's disease, as well as to determine the stage of the disease. Deep Neural Network classifiers are suggested for identifying various phases of Parkinson's disease in comparison to datasets of healthy individuals. This would likely enhance the diagnosis and aid doctors in making prompt intervention decisions for patients with PD. According to the current findings, VGG-16 is effective in classifying MRI data for various stages of Parkinson's disease, at least within the PPMI database.

References:

1. Freddie Åström, Rasit Koker. (2011). A parallel neural network approach to the prediction of Parkinson's Disease, *Expert Systems with Applications*, 38(10),12470-12474, DOI: https://doi.org/10.1016/j.eswa.2011.04.028.
2. Guo Y, Yang J, Liu Y, Chen X, Yang G.Z. (2022). Detection and assessment of Parkinson's disease based on gait analysis: A survey. *Front Aging Neurosci*, 14:916971. https://doi.org/10.3389/fnagi.2022.916971.
3. Hutchinson M, Raff U. (2000). Structural changes of the substantia nigra in Parkinson's disease as revealed by MR imaging, AJNR Am J Neuroradiol. 21(4), 697-701. PMID: 10782780, PMCID: PMC7976637.
4. Korfiatis P, Kline T.L, Lachance D.H, Parney I.F, Buckner J.C, Erickson B.J. (2017). Residual Deep Convolutional Neural Network Predicts MGMT Methylation Status. *J Digit Imaging.* 30(5), 622-628. DOI: https://doi.org/10.1007/s10278-017-0009-z.
5. Malek F, Neuzil P, Gustafsson F, Kaye DM, Walton A, Mates M, Søndergaard L, Ihlemann N, Mariani JA, Reddy V. Clinical outcome of transcatheter treatment of heart failure with preserved or mildly reduced ejection fraction using a novel implant, *Int. J Cardiol*., 187, 227-8 DOI: https://doi.org/10.1016/j.ijcard.2015.03.198.
6. Mehrbakhsh Nilashi, Othman Ibrahim, Hossein Ahmadi, Leila Shahmoradi, A knowledge-based system for breast cancer classification using a fuzzy logic method, *Telematics and Informatics*, 34(4), 133-144, DOI:https://doi.org/10.1016/j.tele.2017.01.007.
7. Nayak, B., Dash, G.P., Ojha, R.K. (2023). Application of Machine Learning Techniques for Detection and Segmentation of Brain Tumors. *SN COMPUT. SCI.* 4, 520. https://doi.org/10.1007/s42979-023-01918-7.
8. Noor, M.B.T., Zenia, N.Z., Kaiser, M.S., A. Mamun, S., Mahmud, M. (2020). Application of deep learning in detecting neurological disorders from magnetic resonance images: a survey on the detection of Alzheimer's disease, Parkinson's disease and schizophrenia. *Brain Inform*. **7**(1), 1–21, DOI: https://doi.org/10.1186/s40708-020-00112-2.

CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632599
http://magellanes.com/

9. P. M. Shah, A. Zeb, U. Shafi, S. F. A. Zaidi and M. A. Shah. (2018). Detection of Parkinson's Disease in Brain MRI using Convolutional Neural Network, *24th International Conference on Automation and Computing (ICAC)*, 1-6, DOI: https://doi.org/10.23919/IConAC.2018.8749023.
10. Sasaki M, Shibata E, Tohyama K, Takahashi J, Otsuka K, Tsuchiya K, Takahashi S, Ehara S, Terayama Y, Sakai A. (2006). Neuromelanin Magnetic Resonance Imaging of locus ceruleus and substantia nigra in Parkinson's Disease, *Neuroreport*, 17(11), 1215-8. DOI: https://doi.org/10.1097/01.wnr.0000227984.84927.a7
11. Varrecchia, T., Castiglia, S. F., Ranavolo, A., Conte, C., Tatarelli, A., Coppola, G., et al. (2021). An artificial neural network approach to detect the presence and severity of Parkinson's disease via gait parameters. *PLoS One.* DOI:https://doi.org/10.1371/journal.pone.0244396
12. Yamashita, R., Nishio, M., Do, R.K.G. et al. (2018). Convolutional neural networks: an overview and application in radiology. Insights Imaging 9, 611–629 (2018). https://doi.org/10.1007/s13244-018-0639-9.