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DEVELOPING AI MODELS TO DIAGNOSIS PARKINSON'S DISEASE (PD) USING MULTINATIONAL MRI

MASTER'S THESIS

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Department of Software Engineering

Artificial Intelligence and Data Science Program

SEPTEMBER, 2023

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INSTITUTE OF GRADUATE STUDIES

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ONAY SAYFASI

DECLARATION

I hereby declare with the respect that the study "DEVELOPING AI MODELS TO DIAGNOSIS PARKINSON'S DISEASE (PD) USING MULTINATIONAL MRI", which I submitted as a Master thesis, is written without any assistance in violation of scientific ethics and traditions in all the processes from the project phase to the conclusion of the thesis and that the works I have benefited are from those shown in the References. (30/10/2023)

ALAA IM ABUKARESH

FOREWORD

“First and foremost, I extend my heartfelt gratitude to God for guiding me through this journey and providing me with the strength and perseverance to complete this thesis. I would also like to express my deepest appreciation to my family, for their unwavering support and encouragement throughout my academic endeavors.

First, I would like to express my endless gratitude to God for being who I am right now and helping me to find patience, strength within myself to complete this thesis.

I would also like to thank my family not only for encouraging me to go abroad for a master’s degree but also for teaching me to chase my dreams and never give up.

I feel very fortunate to have Dr. ALI OKATAN as my supervisor and want to express my appreciation for guiding me within the whole research process in a patient and effective manner.

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SEPTEMBER, 2023 ALAA IM ABUKARE

ÇOK ULUSLU MRI KULLANARAK PARKINSON HASTALIĞINI (PD) TEŞHIS ETMEK İÇIN YAPAY ZEKA MODELLERI GELIŞTIRME

ÖZET

Parkinson Hastalığı (PH), dünya genelinde nüfusun önemli bir bölümünü etkileyen bir nörodejeneratif bozukluktur. PH'nin erken ve doğru teşhisi, etkili tedavi ve hastalık yönetimi için hayati öneme sahiptir. Bu çalışmada, Manyetik Rezonans Görüntüleme (MRI) verilerini kullanarak PH'nin erken aşamada tespit edilmesini amaçlayan bir yapay zeka (YZ) modeli öneriyoruz ve derin öğrenme tekniklerini kullanıyoruz.

Bu araştırmada kullanılan veri Parkinson Hastalığının İlerleme İzleme Girişimi'nden (PPMI) elde edilmiştir ve 1.207 görüntüyü içerir; bunların içinde 919 MRG taraması PH tanısı konmuş bireylerden ve 288 MRG taraması sağlıklı bireylerden elde edilmiştir. Veri önceden işlenir ve modellerin sağlamlığını ve genelleme yeteneklerini artırmak için artırılır.

İki önde gelen aktarım öğrenme modeli olan DenseNet121 ve ResNet, önceden işlenmiş veri üzerinde uygulanır ve eğitilir. Bu modeller, tıbbi görüntülerden yüksek seviye özellikler çıkarma yetenekleri ile bilinir ve çeşitli görüntü sınıflandırma görevlerinde umut vadeden sonuçlar göstermiştir. Bu modellerin önceden eğitilmiş ağırlıklarını kullanarak, belirli PH veri kümemiz üzerinde ince ayar yaparız.

Modellerin performans değerlendirmesi, doğruluk ve F1 skoru gibi standart metrikler kullanılarak yapılır. Sonuçlarımız, hem DenseNet121 hem de ResNet'in PH-etkilenen bireyler ile sağlıklı bireyler arasındaki farkı ayırt etme konusundaki etkililiğini gösteren yüksek doğruluklar elde ettiğini göstermektedir. DenseNet121 %88,50 doğruluk ve 0,8847 F1 skoru elde ederken, ResNet %92,50 doğruluk ve 0,9247 F1 skoru elde eder.

Bu çalışmanın bulguları, özellikle DenseNet121 ve ResNet gibi YZ modellerinin MRI taramalarını kullanarak PH'nin erken teşhisinde klinisyenlere yardımcı olma potansiyeline sahip olduğunu göstermektedir. Bu modellerin elde ettiği

yüksek doğruluklar, görüntüleme özelliklerine dayanarak PH- etkilenen ve sağlıklı bireyler arasındaki farklılığı ayırt etme yeteneklerini göstermektedir. Aktarım öğrenme ve önceden eğitilmiş modellerin kullanılması, büyük miktarlarda etiketli veriye olan ihtiyacı azaltır ve modellerin genelleme yeteneklerini artırır.

Sonuç olarak, bu araştırma MRG verilerini kullanarak PH'nin erken teşhisi için etkili bir yaklaşım sunarak tıbbi görüntüleme ve YZ alanına katkıda bulunur. Önerilen DenseNet121 ve ResNet modelleri umut vadeden sonuçlar sunmakta ve sağlık profesyonellerine doğru PH teşhisinde YZ'nin potansiyelini göstermektedir. Daha büyük ve çeşitli veri kümeleri üzerinde yapılan daha fazla araştırma ve doğrulama, önerilen modellerin gerçek dünya klinik uygulamaları için güvenilirlik ve genelleme yeteneklerini artırabilir.

Anahtar Kelimeler- Parkinson Hastalığı, ikili sınıflandırma, Evrişimli Sinir Ağları, Aktarım Öğrenme, DenseNet121, ResNet, MONAI.

DEVELOPING AI MODELS TO DIAGNOSIS PARKINSON'S DISEASE (PD) USING MULTINATIONAL MRI

ABSTRACT

Parkinson's Disease (PD) is a neurodegenerative disorder that affects a significant portion of the population worldwide. Early and accurate diagnosis of PD is crucial for effective treatment and disease management. In this study, we propose an artificial intelligence (AI) model using deep learning techniques to detect PD at an early stage using Magnetic Resonance Imaging (MRI) data.

The dataset used in this research is obtained from the Parkinson's Progression Markers Initiative (PPMI) and consists of 1,207 images, including 919 MRI scans from individuals diagnosed with PD and 288 MRI scans from healthy individuals. The dataset is pre-processed and augmented to enhance the robustness and generalization of the models.

Two state-of-the-art transfer learning models, DenseNet121 and ResNet, are implemented and trained on the pre-processed dataset. These models are known for their ability to extract high-level features from medical images and have shown promising results in various image classification tasks. We leverage the pre-trained weights of these models, fine-tuning them on our specific PD dataset.

Performance evaluation of the models is conducted using standard metrics such as accuracy and F1 score. Our results demonstrate that both DenseNet121 and ResNet achieve high accuracies, indicating their effectiveness in distinguishing between PD-affected and healthy individuals. DenseNet121 achieves an accuracy of 88.50% and an F1 score of 0.8847, while ResNet achieves an accuracy of 92.50% and an F1 score of 0.9247.

The findings of this study indicate that AI models, particularly DenseNet121 and ResNet, have the potential to assist clinicians in the early detection of PD using MRI scans. The high accuracies achieved by these models demonstrate their ability to differentiate between PD-affected and healthy individuals based on imaging features. The utilization of transfer learning and pre-trained models reduces the need for large amounts of labeled data and enhances the generalization capabilities of the models.

In conclusion, this research contributes to the field of medical imaging and AI by presenting an effective approach for the early detection of PD using MRI data. The

proposed DenseNet121 and ResNet models offer promising results and demonstrate the potential of AI in assisting healthcare professionals in accurate PD diagnosis. Further research and validation on larger and diverse datasets can help enhance the reliability and generalization of the proposed models for real-world clinical applications.

Keywords- Parkinson's Disease, binary classification, Convolutional Neural Networks, Transfer Learning, DenseNet121, ResNet, MONAI**.**

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I. INTRODUCTION

A. Overview

A vital component of human life has always been and will continue to be healthcare. Because of the dreadful and rapid advancement of technology, which affected every part of life, both scientists and medical professionals were keenly interested in how to diagnose diseases.

In addition to helping with disease diagnosis, technology has also been used to perform surgeries and calculate medication dosages.

Biomedical imaging technologies like computed tomography, Magnetic Resonance Imaging, positron emission tomography, and X-rays are used for diseases diagnose.

As a result of the increased use of technology nowadays, The management of expanding imaging data is becoming a problem for healthcare providers.(GREENE, N., ET AL. (2014))

High-performance computational tools, on other hand, accelerate the analysis of biomedical imaging data while reducing the radiologist's burden. Additionally, this technical advancement has made it possible for researchers to work with data and clinical models that are more complicated. (ALSHARABI, NAIF, ET AL.(2023))

The term "neurodegenerative disease" (ND) is widely used to characterize cognitive impairments that impede a person's ability to think, walk, communicate, and learn. ND refers to issues with the brain. Some neurological diseases severely affect brain cells, creating unrelenting suffering that could potentially put a person's life in peril. Therefore, reducing the death rate depends on increasing public knowledge of this ailment and the most prevalent NDs which are typically identified in older persons are Parkinson's disease and Alzheimer disease.

Parkinson's disease is a neurological ailment that progresses over time and is defined by several motor and non-motor symptoms that significantly lower quality of

life. The movement disorder falls under the extrapyramidal disorder category and has no known cause. There are various extrapyramidal illnesses with other causes, such as vascular dementia, injury, sopori c-generate, carbon monoxide toxin, etc. that are categorized as Parkinsonism.

Four main symptoms of the disease—tremors, rigidity, bradykinesia, and postural instability—are caused by the loss of dopaminergic neurons in the substantia nigra and basal ganglia. Depending on how severe the symptoms are, Parkinson's disease is divided into mild, moderate, and advanced categories. Although idiopathic Parkinson's disease affects most patients, 20% are thought to be inherited. Genetic characteristics may distinguish Parkinson's disease subtypes, but more research is required before genetic information can be included in data-driven algorithms.

Parkinson's disease has no known cure, however, the symptoms can be controlled with medicines and surgery. The Hoehn and Yahr (HY) scale and the Uni ed Parkinson's Disease Rating Scale (UPDRS) are two scales used to measure disability and impairment in Parkinson's disease. Parkinson's disease is the most common neurological disorder after Alzheimer's disease. Although the prevalence of Parkinson's disease rises with age, only 4% of patients have the situation when they turn 50. Parkinson's disease is more common in men than in women. (24) Parkinson's disease is thought to afflict 7 to 10 million people worldwide.

The risk of acquiring Parkinson's disease may be increased by excessive exposure to chemicals like pesticides and herbicides.

Computer vision enables machines to think and understand more like people do. Computer vision is a catch-all phrase for all calculations using visual content, such as pixels in photos, videos, and other media. Numerous vision applications for computer vision exist, including computer-aided diagnosis in medicine, autonomous vehicles, and robots that can move and see like people. With the aid of extremely complex vision functions, computers may now act much like a human eye thanks to computer vision technology. With eyes that can collect light, brain receptors that can access it, and a visual cortex that can comprehend it, humans have extraordinary visual abilities. 30 years ago, significant strides have been implemented toward transferring great human visual abilities to machines. These algorithms for vision applications use deep learning and machine learning to analyze visual information similarly to how the

human brain does. Applications for computer vision are in greater demand than ever. There are several repetitive operations in every area, including finance, healthcare, and marketing, that may be quickly automated utilizing computer vision techniques.

The most popular technique and prerequisite for proper diagnosis and treatment of disorders that impact the neurological system is neuro-imaging. To differentiate between common variations, aging-related alterations, and acute/persistent illnesses, this is crucial. As a result, the brain anatomy can be understood and visualised along with the brain tissues. This makes it easier to visualise and comprehend the structural changes in the brain by building representations of the brain from various perspectives.

The investigation of disease heavily relies on the location of anomalies seen on images. The neuro-radiologist then begins studying after identifying the anomalies and merges the imaging results and clinical data, which results in a thorough diagnosis.

Medical imaging has made incredible strides, but there are still many obstacles to overcome because of access restrictions and quality variances. So artificial intelligence and machine learning have become potent tools in recent years, offering algorithms that can resolve categorization issues in neuroimaging data.

One of the most important goals of neuro-imaging techniques produce images of inside body structures to visualise and comprehend the anatomy of internal brain systems without surgery for better examining and diagnosing brain illnesses. There are numerous methods for taking pictures of the brain. The following imaging techniques are used: positron emission tomography (PET), functional magnetic resonance imaging (F-MRI), structural magnetic resonance imaging (S-MRI), resting state magnetic resonance imaging (rs-MRI), and single-photon emission computed tomography scan (SPECT).

These neuro-imaging techniques can produce high-dimensional images of the brain in axial, sagittal, and coronal views. For better diagnosis and therapy, doctors can distinguish between a healthy brain and a damaged brain using the varied ways that these other planes visualise brain structure.

The field of radiology is being revolutionized by the emergence of artificial intelligence (AI), which aims to simplify the process of medical image interpretation. By utilizing computer vision, in which AI systems are capable of automating tasks such as measurements, identifying abnormalities, and analysing relevant anatomical

structures. This transformation technology converts clinical input data into readily interpretable information, facilitating more efficient and accurate radiological diagnoses.

ResNet, AlexNet, LeNet, VGGNet, MobileNet, DenseNet, and GoogLeNet are a few examples of popular CNN-based architectures designed to improve image categorization performance.

Neural Networks, Decision Tree ,Random Forests, Naive Bayes, and Support Vector Machines are other computer vision techniques used in picture classification. In contrast to deep learning techniques, machine learning techniques require intentional feature engineering.

Transfer learning models and neural networks offer the advantage of eliminating the manual feature extraction process. This automation allows deep learning models to fully automate multi-class or binary classification tasks. Even so, when it comes to handling large datasets, these traditional neural networks may encounter certain limitations that can impact their performance, particularly in computer vision tasks.

B. Problem Statment:

Diagnosing Parkinson's disease (PD) poses significant challenges because of the reliance on subjective symptoms and clinometric tests, which lack definitive confirmation. Also, Manual assessment methods are time-consuming, resource-intensive, and require expertise, leading to inconvenience and high patient costs. There are many techniques used to diagnose Parkinson's Disease such as Finger Tapping Tests and handwritten drawings that can identify upper limb impairments but these techniques cannot confirm PD diagnosis. Additionally, PET scans can only detect PD after significant dopamine neuron loss, hindering early intervention. SPECT images, while capable of examining dopamine activity, are limited in their ability to see structural changes, resulting in many false diagnoses. The invasive nature of generating PET or SPECT images with radioactive tracers further restricts their clinical use. Moreover, SWI, which detects PD through brain iron decomposition, is limited by anatomical structures. Furthermore, the availability of smaller datasets for

PD diagnosis hampers accuracy assessment and increases the risk of over-fitting in diagnostic techniques.

Given the rising prevalence of PD and its effects on patients ' lives, it is needed to create a decision-support system to handle these issues. Computational tools, such as Artificial Intelligence techniques, have the potential to assist clinicians deciding accurate decisions regarding PD. Remote patient monitoring through web access and advanced telecommunication systems can reduce the inconvenience and cost of physical visits. Still, reliable clinical monitoring tools are necessary to utilize these opportunities effectively. Speech problems, including slurring and weak voice, are common in PD patients, emphasizing the importance of accurate classification and early prediction. Currently, clinical diagnoses rely on subjective assessments and neurological testing, such as the Unified Parkinson's Disease Rating Scale (UPDRS), which may not be effective in the early stages of PD. Therefore, the development of automated Artificial Intelligence-based methods is essential to improve the accuracy of PD diagnosis and support better decision-making for clinicians.

II. LITERATURE REVIEW

Nowadays, computer-assisted prognosis is more prevalent in the healthcare industry. Even though the diagnosis approach for Parkinson's disease requires taking into account neurological examination and, clinical records, however, there are several studies based on Magnetic Resonance Imaging which is used to diagnose the disease in many literature.

A survey and overview of computer vision methods used to examine neuro-images for neurodegenerative illnesses are provided in specific papers. They discuss how computer vision techniques are used in neuroimaging analysis and how this could affect how neurodegenerative diseases are identified and understood, like the survey proposed by the authors Khan and Kaushik: a comprehensive survey of computer vision techniques used to analyze neuro-images of patients suffering from neurodegenerative diseases. They discuss the growing prevalence of these diseases and the need for early diagnosis and review various computer vision techniques, such as image segmentation, registration, classification, and clustering, that are commonly used in neuro-image analysis. They also highlight the challenges associated with neuro-image analysis and how computer vision techniques can help overcome them. The paper provides a detailed review of various studies and research works in the field of neuro-image analysis using computer vision techniques and emphasizes the potential of computer vision techniques in improving the accuracy and efficiency of neuro-image analysis for neurodegenerative diseases. (KHAN, YUSERA FAROOQ, AND BAIJNATH KAUSHIK,2020)

Additionally, Khan, Yusera Farooq, and Baijnath Kaushik discuss using computer vision algorithms in the analysis of high-resolution medical pictures, particularly neuro-imaging data obtained from modalities like MRI, CT, PET, and SPECT. The focus is on detecting, predicting, and diagnosing neurodegenerative diseases such as Alzheimer’s and Parkinson’s, which involve the progressive deterioration of neuronal cells in the human brain. The article highlights the computer vision techniques and its rols, such as image classification and identification, in

interpreting neuroimaging data. The authors also discuss successful CNN-based architectures such as ResNet, AlexNet, LeNet, VGGNet ,and GoogLeNet which enhance image classification performance. In conclusion, computer vision is emerging as a critical tool to process medical images, enabling more efficient detection, prediction, and diagnosis of neurodegenerative diseases. (KHAN, YUSERA FAROOQ, and BAIJNATH KAUSHIK, 2020)

On the other hand, some articles have been devoted to the categorization of Parkinson's Disease (PD) utilizing MRI data employing deep learning methods, especially Convolutional Neural Networks (CNNs). They emphasise the promise of deep learning in enhancing diagnosis accuracy as they analyze various architectures, approaches, and performance indicators for PD classification. Explores the application of deep learning techniques, particularly Convolutional Neural Networks (CNN), in the categorization of neural brain images to distinguish or identify brains with Parkinson's disease (PD) from healthy brains. The dataset utilized in the study included 24 elderly ordinary control people aged 60 to 75 years old and 30 patients with PD with no history of neurological or medical disorders. As part of the pre-processing steps for the anatomical data, the Brain Extraction Tool was utilised to remove non-brain tissue from T1 anatomical images. After that, the images were converted into a stack of 2D PNG images. In the basic model, the author used three layers of the 2D convolution layer, each with a 'ReLu' activation function, followed by 2-3 max-pooling layers, a flattened layer, and two dense or fully connected layers, with final layer having two neurons corresponding to each of the two output classes (PD or normal). Without batch normalisation, the model's accuracy was 97.63%; with batch normalisation, it was 97.91%. The authors contend that more complex systems or other medical image categorization applications can be successfully implemented using the same architecture. (ROSHNI SAHA, 2019)

Also, Dr. Naif Alsharabi and his team proposed a hybrid model that integrates classical transfer learning and quantum transfer learning to diagnose neurodegenerative diseases using MRI data. The model extracts informative features using a pre-trained AlexNet model and then feeds this network into a quantum variational circuit (QVC) to transform the data into a 2-dimensional vector for binary classification of brain disorders. The AlexNet-quantum learning model achieved high accuracy in classifying Alzheimer's disease and Parkinson's disease when compared

with a classical transfer learning model. The proposed method could provide viable solutions in healthcare, with potential future applications in real quantum hardware devices and multi-classification tasks in computer vision. (ALSHARABI, NAIF, ET AL, 2023)

Developing a 3D convolutional neural network to achieve early diagnose of Parkinson's Disease using 3T T1-weighted MRI scans from the Parkinson's Progression Markers Initiative database was the goal of Sabyasachi Chakraborty. The study found that the created 3D CNN model successed with 95.29% as an overall accuracy, 0.943 as an average recall, average precision of 0.927, and 0.936 for f1-score of every class. This model placed the most emphasis on substantia nigra region of the brain for determining if a given MRI image indicated as Parkinson's Disease. The study concludes that results are encouraging; additionally, researchers need to enhance the detection of Parkinson's Disease using more efficient architectures and specific subcortical structures. (CHAKRABORTY, SABYASACHI, SATYABRATA AICH, and HEE-CHEOL KIM, 2020).

Even though Nikhil J. Dhinagar and his team proposed a deep learning approach for the Parkinson's disease (PD) and Alzheimer's disease (AD) classification depending on 3D T1-weighted brain MRI. The authors used many datasets for training a 3D convolutional neural network (CNN) model, including the Parkinson's Progression Markers Initiative (PPMI), the Alzheimer's Disease Neuroimaging Initiative (ADNI), and the Open Access Series of Imaging Studies (OASIS) dataset. They also applied a random forest classifier as a basic model. For both PD and AD classification tests, the 3D CNN beat the random forest classifier, for PD classification using PPMI test set, the ROC-AUC was 0.667 and for UPenn dataset, they obtained ROC-AUC of 0.743. On the other hand, and for AD classification, when the ADNI test set was used, the ROC-AUC was 0.878, even though using OASIS dataset the average ROC-AUC was 0.789. For unseen MRI data from several data centres, the suggested model also generalised well. The authors suggest that this model could be a useful screening tool before more invasive procedures like PET scans and CSF assays and help distinguish between problematic cases of PD and AD whether their motor and non-motor symptoms are similarly mild. (DHINAGAR, NIKHIL J., ET AL, 2021)

To identify Parkinson's illness using MRI slices, Erdaş, Ç.B., Sümer, E introduce a supervised deep learning technique. The suggested method uses 3D T1-

weighted MR images with median slices in the axial, coronal, and sagittal planes to detect neurodegeneration in the brain. The technique combines an AlexNet architecture and a CNN deep learning model to identify images in this new format. Classification performance of 90.36% accuracy and 90.51% area under the ROC measure was achieved using the suggested strategies. According to the study's conclusions, the suggested method can detect brain degradation on median slices of MR images, is a useful technique to diagnose Parkinson's disease. To strengthen the classifier's stability in future studies, the authors emphasize that new datasets should be added to the block of datasets that are already there. (ERDAŞ, ÇAĞATAY BERKE, AND EMRE SÜMER, 2022)

Sajeeb, Asaduzzaman proposes a prediction model for detecting Parkinson's disease (PD) due to deep learning techniques using neuro-images. To accurately classify PD patients, the model utilizes convolutional neural network (CNN) architectures, including VGG19, ResNet50, and InceptionV3. The study found that VGG19 had the highest accuracy among the three models tested. Further improvement can be made by including more complicated network topologies and convolutional layers in upcoming research, enabling doctors to detect PD more precisely and effectively. (SAJEEB, ASADUZZAMAN, ET AL, 2020)

Veetil, Iswarya Kannoth evaluates the performance of five deep learning architectures for refining the diagnosis of Parkinson's disease using MRI images. Due to the growing accessibility of public information, sophisticated machine-learning algorithms have been created to aid in the classification and preliminary risk assessment of PD’s patients. This study evaluates and contrasts the performance of five deep learning architectures, including VGG16, VGG19, Xception, ResNet50, and DenseNet201, using a variety of performance metrics, including classification accuracy, F1 scores, number of training epochs, model complexity, and depth of the network model. Transfer learning is used as the primary analytical technique. Three of the five models taken into consideration perform noticeably better than the existing work utilising the AlexNet model, according to testing of the models without hyperparameter adjustment. This research demonstrates the possibility of artificial intelligence as a decision assistance system for MRI-based Parkinson's disease diagnosis. (VEETIL, ISWARYA KANNOTH, ET AL, 2021)

(KUMARAN, R., and S. SHANTHINI, 2022) present a hospital application that uses a modified VGG Net architecture to accurately detect Parkinson's disease from MRI scans without needing multiple consultations from different doctors. The project aims to decrease the time and rate of human error associated with manual interpretation of medical images. The methodology involves improving the dataset, which involves MR scans, obtaining a trained model applying the VGG-16 architecture, and efficiently performing classification for patients using different CNN models. The ResNet-50 architecture is the most optimal. A web application with JavaScript framework reactJS is published as a front-end interface for the project. The paper concludes that the project helps cost-effectively provide efficient treatment and prevents the rate of human error associated with manual classification.

In the context of using Deep Learning for Neurodegenerative Disease Diagnosis using Neuro-Images, some papers propose deep learning approaches for the diagnosis of neurodegenerative diseases, such as Alzheimer's Disease (AD) and Parkinson's Disease (PD), using neuro-images. They utilize specific deep learning architectures and explore the potential of graph theoretical metrics and machine learning techniques in diagnosing and prognosis these diseases. Examples of these researchers were:

Kazeminejad, Amirali, Soroosh Golbabaei, and Hamid Soltanian-Zadeh explored the use of graph theoretical analysis and machine learning techniques for the diagnosis of Parkinson's disease (PD) using resting-state functional magnetic resonance imaging (rs-fMRI) data. 19 PD patients and 18 healthy controls are included in the study, and the data undergoes several preprocessing steps before constructing a brain network graph using 90 regions of interest and their average time series. Global graph theoretical metrics are then extracted, including characteristic path length, efficiency, clustering coefficient, transitivity, and small-worldness, to investigate the ways in which PD patients' brain connection is altered. The study finds statistically significant increases in characteristic path length and decreases in segregation metrics and efficiency in PD patients. These alterations are not limited to a specific threshold, indicating aberrant functional connectivity at a larger scale. The study also uses local metrics, including centrality and nodal degree, as features to train a support vector machine classifier. The classifier can achieve a diagnostic accuracy of 95% when subjected to a leave-one-out cross-validation test. The five best features selected by

the floating forward automatic feature selection method related to the cuneus (right hemisphere), precuneus (left), superior (right), and middle (both) frontal gyri, which have all been noted to change in Parkinson's disease previously. Overall, the study confirms that Parkinson's patients' symptoms are correlated with broad changes in their brain networks. and shows the potential of employing machine learning and graph theoretical metrics for identifying diseases.. The findings suggest that PD symptoms are related to dysfunctional networks and the aberrant communication between these networks. (KAZEMINEJAD, AMIRALI, SOROOSH GOLBABAEI, AND HAMID SOLTANIAN-ZADEH, 2017)

And Qiu, Anqi developed a deep learning model, called graph-CNN-RNN, for the prognosis of Alzheimer's disease (AD) using brain structural MRI scans. The model was tested against the Open Access Series of Imaging Studies-3 and the other half of the Alzheimer's Disease Neuroimaging Initiative dataset. With an accuracy of about 80%, the graph-CNN-RNN predicted the conversion to AD from 0 to 4 years before the onset of AD. The positron emission tomography-measured amyloid load and clinical characteristics were both related to the AD probability risk. According to the study, there is a lot of opportunity for clinical applications of the graph-CNN-RNN and the AD probabilistic risk in the prognosis of AD. The model predicts the diagnosis of controls, moderate cognitive impairment, or Alzheimer's disease at each time point and lowers the dimensionality of the cortical thickness data. (QIU, ANQI, ET AL.2022)

Albu, Adriana presents a binary classification algorithm to predicte the presence of malignant lesions in prostate cancer using three-dimensional magnetic resonance imaging (MRI) and convolutional neural networks (CNNs). The paper highlights the need for faster and more accurate diagnosis of prostate cancer, as traditional methods such as biopsies and histopathologic tests are time-consuming and depend on the radiologist's experience. The proposed algorithm reduces the time taken for investigations and could be a starting point in the diagnosis phase. The authors evaluated several models and chose the most performant architecture using the PyTorch and MONAI frameworks, which provide the following:

- Technical support.
- Optimization in training and evaluation phases.

- Compatibility with multiple operating systems.

The following steps for this research involve integrating the model into an application with a graphical user interface and developing algorithms to detect and segment the lesions to improve the application's accuracy. (Albu, Adriana 2023)

Sabyasachi Chakraborty and the research team: aimed to look into the early diagnosis of Parkinson's disease, a neurodegenerative condition brought on by the loss of dopaminergic neurons. The PPMI database of 406 people, half healthy and half of whom had Parkinson's disease, provided the 3T T1-weighted MRI images used in this investigation. The data was pre-processed, and a 3D convolutional neural network (CNN) was developed to learn patterns in the MRI scans for detecting Parkinson's Disease. The 3D CNN developed network performed great average outcomes, with an accuracy of 95.29%, a recall of 0.943, 0.927 precision, 0.943 for specificity, f1-score was 0.936 and ROC-AUC score of 0.98 for both classes. The study shows the possibility of 3D CNNs for early Parkinson's disease detection, which can enhance patient outcomes and lessen the financial burden on governments. (SABYASACHI CHAKRABORTY, SATYABRATA AICH, AND HEE-CHEOL KIM, 2020)

Raj, Sini S., et al., proposed a deep learning-based automated segmentation algorithm to quantify iron accumulation in the deep gray matter structures of the brain in degenerative Parkinsonian disorders. (RAJ, SINI S., ET AL.2019)

Pathological iron deposition is evident in the degenerating brain areas of neurodegenerative disorders such Parkinson's disease, Multiple System Atrophy, and Progressive Supranuclear Palsy, which induce irregularities in bodily movements and posture.The Quantitative Susceptibility Mapping technique can quantify iron deposition, however, manual annotation of areas of interest (ROIs) takes time and may be accompanied by inter-rater differences.The proposed model uses a pre-trained deep learning model called Segnet for pixel-label-based semantic segmentation to automatically segment deep gray matter structures from MRI images, allowing for easy calculation of the amount of iron deposition. This method can effectively aid in precisely quantifying iron deposition, a crucial determining factor in developing Parkinsonian disease in the elderly community. However, the article highlights that While there are numerous ways to make learning on smaller datasets easier, the

remarkable achievements of deep learning still require highly annotated large medical datasets.

Using Transfer learning techniques with Deep neural Networks to detect Parkinson's disease. Using fMRI data, Sakib, A. F. M., Sanjida Ali Shusmita, and S. M. Kabir aimed to detect Parkinson's Disease and distinguish between those with the condition and the control group. They used the integration of Deep Neural Networks and Transfer Learning to develop three models - InceptionV3, VGG16, and VGG19. The models accuracy is compared and evaluated, and the dataset for this research is collected from the Parkinson's Progression Markers Initiative (PPMI) repository. The results indicate that VGG19 gives the best accuracy at 91.5%, followed by InceptionV3 at 89.5% and VGG16 at 88.5%. The input data were amassed from the PPMI database, and MRI images were acquired in slices, which were then processed into the CNN models to extract features from the data group. The prediction model is obtained, and the subjects are tested to determine whether they have PD or are in the control stage. (SAKIB, A. F. M., SANJIDA ALI SHUSMITA, AND S. M. KABIR, 2020)

Anupama Bhan focuses on the early diagnosis of Parkinson's disease using brain MRI data and employs a deep learning algorithm for detection. This paper describes using a deep learning algorithm the detection of Parkinson's disease in brain MRI images. MRI can capture changes in the brain structure due to dopamine deficiency. Early diagnosis is crucial for effective treatment, and computer-aided diagnosis can assist clinicians in achieving this objective. The study uses a Convolutional Neural Network (CNN) with the LeNet-5 architecture to classify MRI data of Parkinson's disease subjects from normal controls. Dataset contained 10,548 images, and the model achieved 97.92% as an accuracy with batch normalization and dropout algorithms. The study concludes that this method can be used for diagnosing different stages of Parkinson's disease, and the model's accuracy can be further optimized by changing the number of neurons, kernel size, and layers and using the dropout algorithm. This research has the potential to facilitate feature extraction, selection, and classification for the prediction of new data in medical and neuroimage analysis. (ANUPAMA BHAN, SONA KAPOOR, MANAN GULATI, AYUSH GOYAL, 2021)

On the field of Classification of PD using Machine Learning and Medical Imaging , there have been many studies, most notably were in the following:

A Bayesian Optimisation Support Vector Machine (BO-SVM) model is presented by Elshewey, Ahmed M., et al. for identifying Parkinson's disease (PD) patients and non-patients. SVM, Random Forest, Logistic Regression, Naive Bayes, Ridge Classifier, and Decision Tree are six machine learning models that the proposed approach uses Bayesian Optimisation to optimize the hyperparameters. 23 features and 195 cases make up the dataset used in this study. The trial findings showed that the SVM model generated the best results with an accuracy of 92.3% after hyperparameter modification using BO. The potential of using BO to improve the accuracy of machine learning models for categorizing PD is highlighted by this work. (ELSHEWEY, AHMED M., ET AL, 2023)

Çağatay Berke Erdaş and Emre Sümer propose a supervised deep-learning method to detect neurodegeneration in the brain, particularly the substantia nigra, using median slices from 3D T1-weighted MR images. This method achieved 90.36% as an accuracy, an area under the ROC curve of 90.51%, a precision of 90.08%, a sensitivity of 90.52%, and 90.25% for F1 score for the classification of Parkinson's disease patients from a control group of healthy individuals. The promising results indicate that computer-aided diagnosis based on medical images can be effective for Parkinson's disease detection. However, they pointed out certain drawbacks, such as the loss of proportion in resized sliced slices and the classifier's dangerous operation due to insufficient Neurocon and Taowu MRI Data Set samples. Adding more datasets is required to enhance the performance of the approach. (ÇAĞATAY BERKE ERDAŞ, EMRE SÜMER, 2022)

Roshni Saha, working on her thesis "Classification of Parkinson's Disease Using MRI Data and Deep Learning Convolution Neural Networks," discusses the use of deep learning algorithms, specifically Convolution Neural Networks (CNNs), for the classification of neural brain images to identify Parkinson's Disease affected brains from normal healthy brains. The accuracy reported by the author for separating MRI data from PD patients from normal controls was 97.63% without batch normalisation and 97.91% with batch normalisation. The study contends that CNN can efficiently classify additional medical images or more sophisticated systems and has the capacity to extract the most discriminative elements from complex clinical data. The method,

according to the author, can also be used to forecast different Parkinson's disease stages for people of different ages and to research dementia and cognitive decline associated with Parkinson's disease. (ROSHNI SAHA, 2019)

Focusing on Parkinson's disease classification using convolutional neural networks applied to SPECT imaging data. Jigna Hathaliya a classification model for Parkinson's disease using single-photon emission computerized tomography (SPECT) imaging data and a convolutional neural network (CNN). Based on the amount of dopamine in the brain, the model hopes to categorise patients and reduce the resources consumed while maintaining the model's performance. Data amplification was used to balance the unbalanced dataset and was preprocessed from the Parkinson's Progressive Markers Initiative (PPMI) dataset. Input layers, convolutional layers, max-pool layers, flattened layers, and dense layers with various dimensionalities are among the 14 layers in the proposed model. The dense layer divides the patients into four groups: GenReg PSD from the full SPECT imaging dataset, PSD, healthy controls, scans without evidence of dopaminergic deficit (SWEDD), and PSD. With 58,692 photos for training, 11,738 images for validation, and 7826 images for testing, a sizable dataset was used to train the proposed model. With an accuracy of 0.889, recall of 0.9012, precision of 0.9104, and F1-score of 0.9057, the suggested model beats the classification models from the surveyed articles. (JIGNA HATHALIYA, NISARG PATEL, RAJESH GUPTA, AND SUDEEP TANWAR, 2022)

Applied to DaTscan pictures, an ensemble of convolutional neural network models, Kurmi, A. presents an ensemble of Deep Learning models for detecting Parkinson's Disease (PD) using DaTscan images. They classified Parkinson's illness using four models—VGG16, ResNet50, Inception-V3, and Xception—and then improved the model's overall performance by using a Fuzzy Fusion logic-based ensemble technique. The Parkinson's Progression Markers Initiative's (PPMI) publicly accessible database is used to assess the suggested model. The suggested model outperforms the individual model in terms of attained recognition accuracy, Precision, Sensitivity, Specificity, and F1-score, which are each 98.45%, 98.84%, 98.84%, 97.67%, and 98.84%, respectively. A GUI-based software tool that rapidly and somewhat accurately detects all classes using magnetic resonance imaging (MRI) has also been created by the authors for public usage. The suggested strategy outperforms existing cutting-edge techniques for detecting PD. Future work by the authors intends

to expand their research to include MRI and CT images. (KURMI, A.; BISWAS, S.; SEN, S.; SINITCA, A.; KAPLUN, D.; SARKAR, R., 2022)

Tarjni Vyas presents a deep learning-based scheme to diagnose Parkinson's disease (PD) using brain images from magnetic resonance imaging (MRI). The authors use two novel approaches using 2D and 3D convolution neural networks (CNN) trained on MRI scans in the axial plane, preprocessed using bias field correction, histogram matching, Z-score normalization, and image resizing. The dataset was collected from Parkinson's progression markers initiative (PPMI). The 3D CNN model achieved a higher accuracy of 88.9% with 0.86 area under the curve (AUC) compared to the 2D CNN model's accuracy of 72.22% with 0.50 AUC. By separating PD patients from healthy controls, the authors come to the conclusion that deep learning models can be employed for early detection. The scientists want to improve the accuracy and other evaluation metric values of the DL model in the future by training the models with GPU parallelization, allowing for more significant sized input in all three dimensions and a greater set of MRI scans in lower times. (TARJNI VYAS, RAJ YADAV, CHITRA SOLANKI, RUTVI DARJI, SHIVANI DESAI, and SUDEEP TANWAR, 2022)

Hybrid techniques that combine segmentation and classification techniques were used for the Detection and classification of Neurodegenerative Disorders from MRI images by B. Selvaganesh & R. Ganesan: who proposed a hybrid segmentation and classification technique for detecting neurodegenerative disorders from brain MRI images. The proposed methodology integrates Particle Swarm Optimization (PSO) and Self-Organizing Map (SOM) techniques for efficient image segmentation, followed by Neighbor Intensity Pattern (NIP) feature extraction and integrated Neural Network and K-Nearest Neighbor (KNN) classification techniques for normal and abnormal region classification. The performance was evaluated using two different datasets, ADNI and PPMI, and compared with traditional classification techniques. The results show that the proposed NN-KNN technique outperforms other methods with an accuracy level of 98.6%, sensitivity rate of 95%, specificity rate of 96%, and precision rate of 99.21%. The paper suggests that the proposed framework can be expanded to classify other brain diseases using advanced techniques in the future.(B. SELVAGANESH & R. GANESAN, 2022)

Mahsa Ghorbani and the research team introduce a novel graph convolutional network (GCN) called RA-GCN for disease prediction problems, particularly addressing imbalanced data. Using graph-based classifiers, they proposed a Re-weighted Adversarial Graph Convolutional Network (RA-GCN) to address the class imbalance in disease prediction problems. The proposed method associates a graph-based neural network to each class to weigh the class samples and prevent the classifier from emphasizing any particular class. An adversarial approach trains the parameters of the classifier and weighting networks. The research presents experimental results on synthetic and three publicly available medical datasets to show that RA-GCN is superior to current approaches in determining the patient's state on all three datasets. The research also points out that creating the best graph necessitates enough samples, which can be scarce in datasets with inequities. When the graph is constructed during training, the findings demonstrate that the suggested technique performs better than others. The learned graph from GCN-unweighted is said to have negatively impacted the results of DR-GCN, which is why it performs poorly. (GHORBANI, MAHSA, ET AL, 2022)

Other studies focus on detecting prodromal Parkinson's disease using fMRI data and deep neural network approaches, like Farhan Shahriar, who discuss deep learning techniques to detect Prodromal Parkinson's Disease (PD) in patients in his paper. The study aims to detect the disease early to alleviate its consequences. The researchers collected fMRI data from 20 Prodromal PD patients and 20 healthy control subjects from the PPMI website. They used deep convolutional neural network architectures to achieve their goal, including mobilenet v1, inception v3, vgg19, and inception resnet v2. They found that the mobile net v1 had the highest classification accuracy of 81.22%, while inception resnet v2, inception v3, vgg19, and ensemble models achieved 75.30%, 62.55%, and 63.32% accuracy, respectively. The study concludes that deep learning techniques can be used to classify image data, even with previously unseen data accurately, and can successfully classify Prodromal PD patients from healthy controls. (FARHAN SHAHRIAR, AMARTTYA PRASAD DEY, NAIMUR RAHMAN, ZARIN TASNIM, and MOHAMMAD ZUBAYER TANVIR, 2021)

As for using Vocal Features extracted from speech signals and employing a random subspace classifier ensemble for classification purposes, some papers like A.

Esk Adere, A. Karatutlu, and C. Aenal are working on a study titled "Detection of Parkinson's disease from vocal features using random subspace classifier ensemble," the base classifier utilized by the scientists was the k-NN. There were 1040 record files of 40 people, 40 of whom were healthy and 40 of whom had PD in their dataset, including train and test data. Their work classified people as healthy (class 0) or PD-affected (class 1). They used Matlab to implement all the algorithms, including kNN, LDA, and QDA. They looked at the ideal parameters utilizing an ensemble method called random subspace to improve classification accuracy. Their lowest categorization error rate was 27.65%. (A. ESK ADERE, A. KARATUTLU, AND C. AENAL, 2015)

And M. Su and K. Chuang developed feature selection for classifying PD speech patterns. Their information was voice-based. The authors used a dataset with two groups. There were 20 participants in the first group of PD sufferers, including six females and 14 males. Ten females and ten males were in the second group, which was in good health. LDA was employed in their paper to assess the effectiveness of feature selection. Jitter, Shimmer, AC NTH, HTN, Median pitch, Mean pitch, Standard deviation, Minimum pitch, Maximum pitch, etc., were only a few features. The authors concluded that fuzzy entropy may be used to eliminate unimportant features. (M. SU and K. CHUANG, 2015)

Despite the many and continuous attempts by researchers to help in the early detection of PD, there are many difficulties and limitations associated with existing detection and screening methods.

Ketna Khanna's discussion and review led the scientists to conclude that a non-invasive, accurate Parkinson's disease screening method is urgently needed. Current methods rely on the observation of symptoms by doctors, which may need to be more accurate and reliable. Several approaches have been proposed using various modalities, but each has limitations, and none can be used in isolation. For instance, PET and SPECT scans are invasive and can cause harm to patients, while FTT and handwritten drawings can only detect upper limb impairments. Voice signals could be more reliable for PD detection. Recently, MRI sequences have been used for PD detection, but their accuracy is still relatively low. Therefore, a more effective and trustworthy method for Parkinson's disease identification with a lower risk of

misclassification is urgently needed. (KETNA KHANNA, SAPNA GAMBHIR, MOHIT GAMBHIR, 2020)

III. BACKGROUND STUDY

A. Parkinson’s Disease.

1. Introduction

Millions of people worldwide are afflicted by the ordinary and crippling neurological condition known as Parkinson's disease (PD). Motor symptoms include tremors; bradykinesia (slow movement), rigidity, and postural instability are what make it distinctive. PD also consists of several non-motor symptoms, have cognitive decline, mood swings, sleep issues, and autonomic dysfunction. The prevalence of Parkinson's disease in society is substantial, with significant implications for affected individuals, their families, and healthcare systems globally. According to the Parkinson's Foundation, approximately 10 million people worldwide live with PD, projected to rise due to population aging. In the United States alone, the estimate exceeds one million individuals.

The historical background of Parkinson's disease dates back to 1817 when Dr. James Parkinson published his seminal essay, "An Essay on the Shaking Palsy." This groundbreaking work provided a detailed clinical description of individuals experiencing characteristic tremors and mobility issues, now recognized as PD's cardinal symptoms. Dr. Parkinson's observations laid the foundation for subsequent research and understanding of the disease. Over the years, advancements in PD research have contributed to the development of treatment options and a deeper understanding of the underlying mechanisms.

The research aims to design a new deep learning system using magnetic resonance imaging (MRI) to detect Parkinson's disease in its early stages. By harnessing the potential of deep learning algorithms, this research aims to analyse MRI scans and extract meaningful features that can distinguish individuals with early-stage PD from healthy controls or those with similar movement disorders. Developing an accurate and efficient deep learning system promises to provide a non-invasive, accessible, and reliable tool for early PD diagnosis, facilitating timely intervention and

potentially slowing disease progression. By addressing this crucial aspect of PD diagnosis, this thesis seeks to contribute to advancing medical imaging technology and enhancing the understanding and management of Parkinson's disease.

2. Symptoms and Diagnosis

Figure 1: Typical appearance of PD

a) Parkinson's Disease is characterized by a range of cardinal motor symptoms that significantly impact the daily functioning of individuals. Tremors are rhythmic, involuntary shaking movements that often occur at rest and commonly affect the hands, fingers, or limbs. Bradykinesia, or slow movement, is a reduced ability to initiate and execute voluntary activities smoothly. Rigidity refers to stiffness and resistance experienced in the muscles, making it challenging to perform tasks requiring flexibility. Postural instability, marked by impaired balance and coordination, increases the risk of falls in individuals with PD.

b) Numerous motor and non-motor symptoms of Parkinson's disease increase the condition overall severity. Cognitive impairment, ranging from mild memory and attention issues to more severe dementia, is a prevalent non-motor symptom. Mood issues, such as anxiety and sadness, are prevalent in PD and can significantly reduce a person's quality of life. Insomnia, restless legs syndrome, and rapid eye movement sleep behaviour disorder are common sleep problems. Autonomic dysfunction, which impacts a number of physiological functions such as bladder control, digestion, and blood pressure regulation, is widespread in PD.

c) Diagnosing Parkinson's Disease relies on clinical assessments and the fulfillment of specific criteria. UK Brain Bank and the Movement Disorder Society (MDS) are

the most commonly used diagnostic criteria. These criteria demand the presence of bradykinesia in addition to a minimum one other cardinal motor symptom (tremor, rigidity, or postural instability). However, given the complexity of PD, the diagnosis is often challenging, particularly in the early stages when symptoms may be subtle. Clinical assessments, including detailed medical history, neurological examination, and response to dopaminergic medication, play a crucial role in diagnosis. While there are currently no specific biomarkers available for routine clinical diagnosis, ongoing research aims to identify potential biomarkers through neuroimaging, genetic testing, and other approaches, which may aid in early detection and accurate diagnosis.

3. Pathophysiology

a) Complex interaction of underlying systems influences the pathogenesis of Parkinson's disease (PD). One such process is the slow degeneration of dopaminergic neurons in the substantia nigra region of the brain. Dopamine, a neurotransmitter that promotes fluid and coordinated movements, is produced by these neurons and is essential for its production. The motor symptoms of Parkinson's disease (PD) are brought on by a severe drop in dopamine levels brought on by the destruction of dopaminergic neurons.

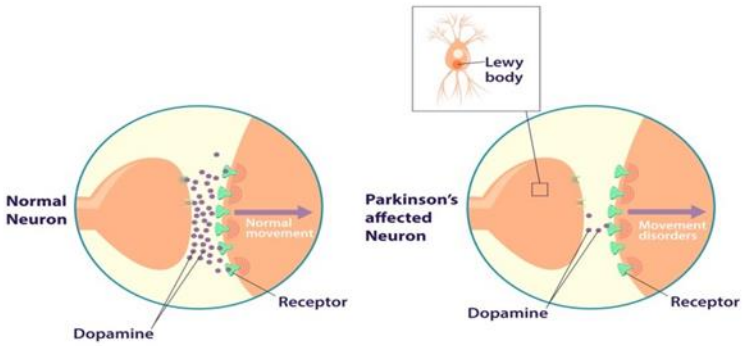

Figure 2: Dopamine levels in a normal and PD affected neuron

b) The formation of Lewy bodies and abnormal protein aggregates is another hallmark pathological feature of Parkinson's Disease. Alpha-synuclein, a protein normally found in nerve cells, accumulates and undergoes misfolding, leading to alpha-synuclein aggregation into Lewy bodies. These Lewy bodies disrupt cellular processes and contribute to neuronal dysfunction and degeneration, further exacerbating PD's motor and non-motor symptoms.

c) Other contributing variables have been connected to the pathophysiology of Parkinson's disease (PD), the loss of dopaminergic neurons, and the aggregation of alpha-synuclein. The gap between the creation of reactive oxygen species and the antioxidant defense system, or oxidative stress, causes cell death and brain impairmentPD has also been linked to mitochondrial dysfunction, which includes reduced energy generation and increased oxidative stress inside mitochondria. Furthermore, neuroinflammation, involving the activation of immune cells and the release of inflammatory molecules in the brain, contributes to the progression of PD by exacerbating neuronal damage and promoting neurodegeneration.

Parkinson's disease has a complicated and multifaceted pathogenesis involving the loss of dopaminergic neurons, alpha-synuclein aggregation, oxidative stress, mitochondrial dysfunction, and neuroinflammation. Understanding these underlying mechanisms is crucial for developing targeted therapeutic strategies that can slow down or halt the progression of the disease.

4. Risk Factors and Epidemiology

a) Both hereditary and environmental variables impact risk factors for Parkinson's disease (PD). The development of PD has been linked to several genes, including SNCA, LRRK2, PARK2, and PINK1. Mutations or changes in these genes may increase a person's susceptibility to PD. A higher risk of PD has also been linked to environmental variables such as exposure to pesticides, heavy metals, certain chemicals, and head injuries. The complex etiology of the disease is likely a result of how environmental variables and genetic predisposition interact.

b) Age, gender, and family history have all been identified as crucial variables in the emergence of PD. The incidence and prevalence of Parkinson's disease (PD) rise with age, making it the most critical risk factor. Although incidences of early-onset PD do exist, they are more common in those patients over 60. Though the exact causes of this gender disparity are not yet entirely known, men are often more likely than women to develop PD. Another significant risk factor for PD is family history since those with PD-affected relatives are at a higher risk of contracting the illness. Understanding these demographic and familial characteristics can provide insights into the underlying causes and probable susceptibility of various groups to PD.

c) Parkinson's Disease has a global impact, with variations in its prevalence and incidence across different regions. The global prevalence of PD is estimated to be around 1% of the population over 60. However, these rates can vary among countries and regions due to genetic, environmental, and demographic differences. Some areas, such as North America and Europe, have reported higher prevalence rates than other parts of the world. Additionally, there may be variations in the incidence of PD, which refers to the number of new cases diagnosed per population per year. Accurate and up-to-date epidemiological data is essential for understanding the burden of PD, identifying potential risk factors, and developing appropriate healthcare strategies for affected populations

5. Treatment Options

a) Parkinson's Disease (PD) management involves a range of therapeutic approaches. Medications form the foundation of treatment, with levodopa being the most effective medication for controlling motor symptoms. Dopamine agonists, like pramipexole and ropinirole, can be used as monotherapy or in combination with levodopa. Other drugs, such as COMT and MAO-B inhibitors, enhance the efficacy of levodopa or manage specific symptoms. Surgical interventions like deep brain stimulation (DBS) can be considered in advanced cases. DBS involves the implantation of electrodes in particular brain regions to regulate abnormal neuronal activity and alleviate motor symptoms. Non-pharmacological strategies, including physical therapy, occupational therapy, and speech therapy, play a crucial role in managing motor and non-motor symptoms, improving functional abilities, and enhancing the overall quality of life for individuals with PD.

b) Ongoing research and emerging therapies hold promise for improving Parkinson's Disease treatment. Gene therapies aim to modify or replace PD-associated genes to slow disease progression. Stem cell transplantation techniques explore the potential of replacing damaged or lost dopaminergic neurons using stem cells. Neuroprotective methods try to slow down or stop the neurodegenerative process in Parkinson's disease (PD) by modifying neuroinflammation or focusing on alpha-synuclein aggregation. These emerging therapies are at various stages of development and clinical trials, offering potential future options for PD management.

c) Despite the available treatment options, challenges and limitations exist in Parkinson's Disease management. Levodopa, while effective, can be associated with long-term complications such as motor fluctuations and dyskinesias. Surgical interventions like DBS have associated risks and may not be suitable for all individuals. Non-pharmacological strategies may require regular adherence and accessibility to specialized healthcare services. Moreover, existing treatments focus on symptom management rather than modifying the underlying disease process. Additionally, individual responses to treatments can vary, highlighting the need for personalized and tailored approaches to PD management. Addressing these challenges and developing more effective and disease-modifying treatments remains a key focus in PD research.

6. Impact on Quality of Life and Caregiver Burden

a) Parkinson's Disease (PD) profoundly impacts the quality of life of individuals living with the condition. Physical symptoms, like tremors, rigidity, and bradykinesia, can significantly impair mobility, independence, and overall functioning. PD also affects emotional well-being, as individuals may experience depression, anxiety, frustration, and a sense of loss due to the disease's progressive nature. Socially, PD can lead to social isolation, reduced participation in activities, and challenges in interpersonal relationships. The combination of these physical, emotional, and social factors often results in a diminished overall quality of life for individuals with PD.

b) Caregivers of individuals with PD face unique challenges and significant burdens. Providing care for someone with PD requires substantial physical, emotional, and time commitment. Caregivers may need to assist with daily activities, manage medications, accompany individuals to medical appointments, and provide emotional support. The progressive nature of PD adds to the caregiver's burden as they witness the deterioration of their loved one's health and functioning. Caregivers may experience increased stress, fatigue, social isolation, and compromised personal well-being. The demands of caregiving can also disrupt their work-life balance and financial stability.

c) Recognizing the impact on both individuals with PD and their caregivers, multidisciplinary care and support services are crucial. A team of medical experts,

including neurologists, physical therapists, occupational therapists, speech therapists, psychologists, and social workers, participate in an interdisciplinary approach, working collaboratively to address the diverse needs of individuals with PD.

This comprehensive approach ensures holistic care, focusing on symptom management, addressing emotional well-being, optimizing physical function, and enhancing overall quality of life. Support services, such as support groups, educational programs, respite care, and counseling, are vital in providing information, guidance, and emotional support to individuals with PD and their caregivers, fostering resilience and coping strategies.

7. Future Directions

a) Parkinson's Disease (PD) research is continuously advancing, opening up promising areas for improving PD management. One area of research focus is the development of novel therapeutic targets and interventions. Ongoing studies explore potential advancements in gene therapies, aiming to correct genetic abnormalities or modulate disease-related genes. Stem cell research holds promise for regenerative approaches to replace damaged neurons and restore normal brain function. Additionally, advancements in neuroprotective strategies, targeting alpha-synuclein aggregation, mitochondrial dysfunction, or neuroinflammation, offer potential disease-modifying approaches that could slow down or halt disease progression.
b) Precision medicine and personalized therapies are emerging as essential strategies for optimizing PD management. Precision medicine involves tailoring treatment approaches based on individual characteristics, such as genetic profiles or biomarkers, to maximize effectiveness and minimize side effects. Personalized therapies may encompass individualized medication regimens, deep brain stimulation settings, or specific rehabilitation plans based on the unique needs of each person with PD. By embracing these approaches, the potential for more targeted and effective treatments is increased, leading to improved outcomes for individuals with PD.

c) Early detection and intervention are pivotal in improving outcomes for individuals with PD. Research efforts are directed toward identifying reliable biomarkers and developing sensitive diagnostic tools to detect PD in its earliest stages, even before the onset of noticeable symptoms. Early intervention strategies, such as neuroprotective agents, lifestyle modifications, and targeted rehabilitation programs, are being explored to potentially delay disease progression and mitigate the impact of symptoms on individuals' lives. By promoting early detection and intervention, there is an opportunity to implement timely and personalized treatments, enhance symptom management, and potentially alter the natural course of PD.

d) Addressing these future directions in Parkinson's Disease research, including advancements in therapeutic targets, precision medicine, personalized therapies, disease-modifying approaches, and the importance of early detection and intervention, holds significant promise in improving the lives of individuals with PD and shaping the landscape of PD.

B. Human Brain Structure

The human brain, which controls the neurological system, is an astonishingly complicated organ. It regulates a range of physical processes, mental operations, feelings, and actions. Understanding the fundamental causes of neurological illnesses like Parkinson's Disease (PD) requires a comprehensive knowledge of the anatomy of the brain.

1. Brain Structure Details

a. Substantia Nigra

The substantia nigra is a midbrain structure that plays a crucial role in movement control. It contains a population of dopaminergic neurons that generate and release dopamine, a neurotransmitter engaged in regulating motor functions. In Parkinson's Disease, the substantia nigra undergoes progressive degeneration, leading to a significant reduction in dopamine levels. This dopamine deficiency contributes to the motor symptoms observed in PD, including tremors, rigidity, bradykinesia, and postural instability.

b. Basal Ganglia

Deep inside the brain is a complex network of structures known as the basal ganglia. It contains the substantia nigra, subthalamic nucleus, globus pallidus, and striatum. The basal ganglia regulate muscle tone, motor coordination, and voluntary movement. The basal ganglia circuitry's delicate balance of neurotransmitters is upset by the loss of dopaminergic neurons in PD, which causes the disease's characteristic motor symptoms.

c. Lewy Bodies

Most abnormal protein clusters known as Lewy bodies are composed of alpha-synuclein. They exist in the brain cells of PD patients and are a pathogenic sign of the disease. Lewy bodies are thought to obstruct biological functions, which may lead to the decline of dopaminergic neurons in the substantia nigra and other regions of the brain. Their existence is closely related to the beginning and progression of PD.

d. Dopaminergic Pathways

A chemical called dopamine is used in the brain's dopaminergic pathways. The dopaminergic pathway primarily affected by PD is the nigrostriatal pathway. This tract links the substantia nigra to the striatum, a region of the basal ganglia involved in motor control. When dopaminergic neurons in the substantia nigra are destroyed[(41)], dopamine signaling in a nigrostriatal way is disrupted, leading to an imbalance that affects the ability to control voluntary movements.

Understanding the specific brain structures involved in Parkinson's Disease provides insights into the underlying pathophysiology of the condition. The interplay between the substantia nigra, basal ganglia, Lewy bodies, and dopaminergic pathways contributes to the motor symptoms and neurodegeneration observed in PD. Advancements in research continue to deepen our understanding of these structures, facilitating the development of novel therapeutic approaches aimed at restoring dopamine function, alleviating symptoms, and potentially slowing down disease progression

C. Image Processing

Image processing refers to applying various techniques to manipulate and analyze digital images. It encompasses several stages, including image acquisition, enhancement, restoration, morphological processing, segmentation, object recognition, representation, and description.

1. Image Acquisition

Image acquisition involves capturing images from different sources, such as cameras, scanners, or medical imaging modalities. In the context of PD, medical imaging techniques like MRI, PET, or SPECT are used to acquire images of the brain, providing valuable information about structural and functional changes.

2. Image Enhancement

Image enhancement techniques aim to improve the visual quality and clarity of images. These techniques include contrast enhancement, noise reduction, sharpening, and image fusion. In PD research, image enhancement can enhance the visibility of brain structures, making it easier to identify and analyze regions of interest.

3. Image Restoration

Image restoration techniques are employed to remove or reduce distortions, artifacts, or noise that may be present in the acquired images. These techniques help to recover the original information that may have been corrupted during the image acquisition process. In PD research, image restoration can improve the accuracy and reliability of subsequent analyses.

4. Morphological Processing

Morphological processing involves operations such as dilation, erosion, opening, and closing, which are applied to images to extract or modify specific features based on their shape or structure. These operations are useful for tasks such as edge detection, shape analysis, and region-based analysis in PD research.

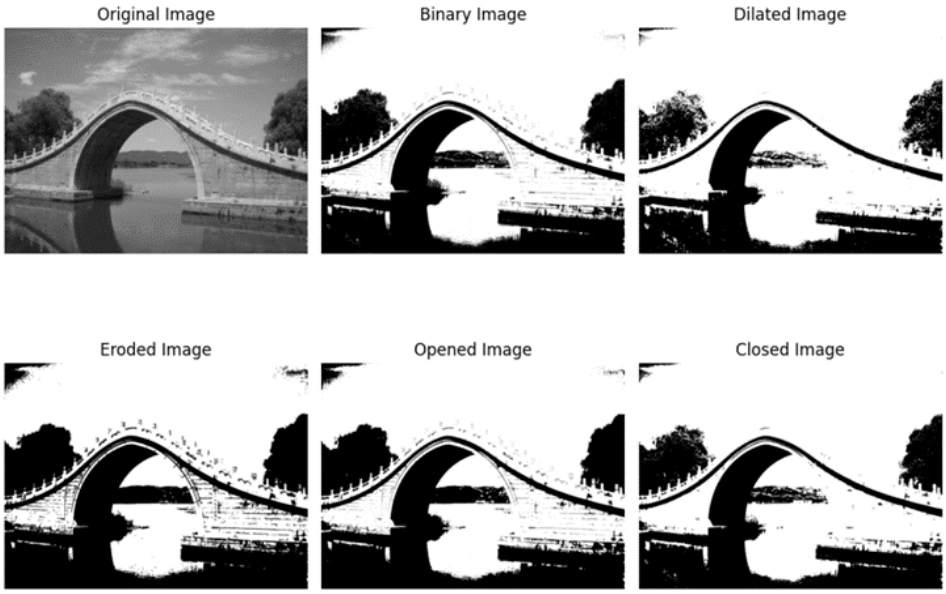

Figure 3: Morphological image processing

5. Segmentation

Segmentation techniques aim to partition an image into meaningful regions or objects. In PD research, segmentation is used to delineate specific brain structures, identify regions affected by abnormalities, or isolate areas for further analysis. Standard segmentation methods include thresholding, region-growing, and active contour models.

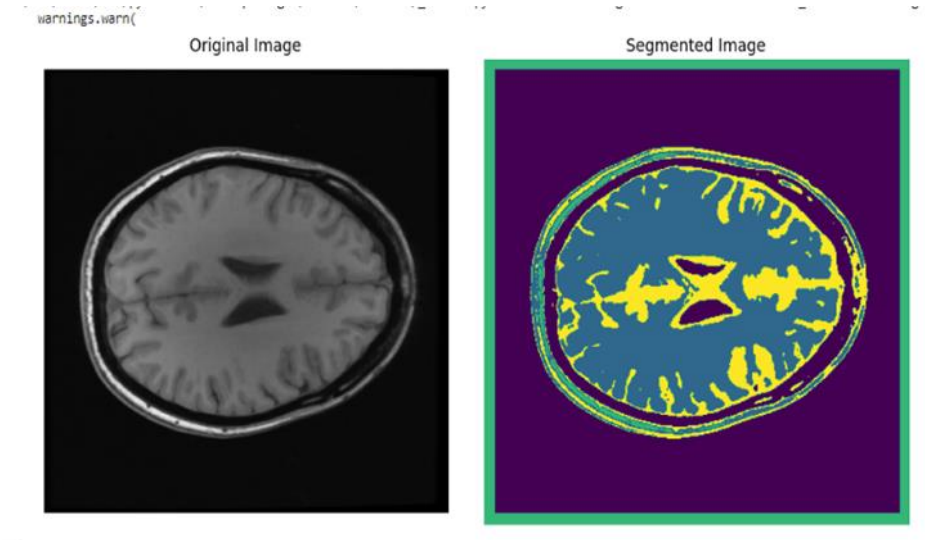

Figure 4: MRI Segmentation

6. Object Recognition

Object recognition techniques identify and classify specific objects or patterns within an image. In the context of PD research, object recognition may involve identifying and classifying particular brain regions or abnormalities associated with PD, such as the substantia nigra or Lewy bodies.

7. Representation and Description

Techniques for representation and description concentrate on succinctly and meaningfully expressing visual attributes. To do this, pertinent traits or descriptors that effectively convey an image's essential details must be extracted. For quantitative analysis and comparison in PD research, representation, and description techniques can be used to quantify the anatomical or functional changes in the brain.

D. Medical image processing

The use of digital image processing techniques on just medical images for study, analysis, and diagnostic purposes is referred to as "medical image processing." Medical image processing is essential for understanding the underlying brain alterations in PD and is helpful for illness diagnosis, observation, and treatment evaluation.

1. Image Pre-processing

Medical images are more reliable and highly quality, thanks to image pre-processing techniques. This comprises techniques for denoising data to lower noise and artifacts that could obstruct accurate analysis. To assure spatial consistency, image registration algorithms match images from several modalities or time points. The alignment of the pictures is improved, and motion-related artifacts are decreased, thanks to motion correction techniques that account for patient movements during image acquisition. Standardizing picture intensity levels with normalization techniques enables more precise quantitative analysis.

2. Segmentation and Region of Interest (ROI) Analysis

Segmentation techniques are applied to medical images to delineate specific brain regions or abnormalities associated with PD. This can involve manual or semi-

automated methods, such as thresholding, area growing, or active contour models. Segmentation allows for the extraction of quantitative measurements within these specific regions, enabling the analysis of structural changes, volumetric measurements, or functional characteristics.

3. Feature Extraction and Quantitative Analysis

Feature extraction methods extract meaningful information from medical images for quantitative analysis. These methods encompass various techniques, such as shape analysis, texture analysis, and intensity-based measurements. Shape analysis involves extracting geometric features, such as size, volume, or curvature, to characterize anatomical structures or detect abnormalities. Texture analysis quantifies the spatial variations in pixel intensities, providing information about tissue heterogeneity or patterns. Intensity-based measurements capture statistical properties of image intensities within specific regions of interest. These extracted features serve as quantitative measures for classification, disease progression tracking, identification of imaging biomarkers, or correlation with clinical outcomes in PD.

4. Machine Learning and Deep Learning

Machine learning and deep learning techniques have gained significant attention in medical image processing for PD. These approaches utilize algorithms to learn patterns and relationships directly from medical image data. Machine learning algorithms, as support vector machines (SVM), random forests, or neural networks, can be trained on labeled datasets to classify images, segment specific structures, or predict disease progression. Deep learning, particularly with convolutional neural networks (CNNs), has remarkably succeeded in medical image analysis. CNNs can automatically learn hierarchical representations from medical images, enabling tasks such as image classification, segmentation, and object recognition in PD research.

5. Image Fusion

Image fusion techniques combine information from multiple imaging modalities or different image acquisition techniques to generate a single integrated image. This fusion enhances complementary knowledge and improves the overall interpretation of medical images. In the context of PD, image fusion can integrate

structural and functional information from MRI, PET, or SPECT scans, providing a more comprehensive view of the disease-related changes in the brain.

Medical image processing techniques in PD research enable researchers and clinicians to extract quantitative measurements, identify structural or functional abnormalities, track disease progression, and develop imaging-based biomarkers. These techniques contribute to accurate diagnosis, personalized treatment planning, and the assessment of treatment efficacy in PD patients.

E. Neuro-Imaging Techniques

Neuroimaging techniques play a crucial role in understanding the structural, functional, and biochemical changes associated with Parkinson's Disease (PD). These techniques provide valuable insights into the underlying mechanisms of the disease, aid in early diagnosis, track disease progression, and evaluate treatment efficacy. Several neuroimaging modalities are commonly used in PD research.

1. Magnetic Resonance Imaging (MRI)

MRI, a non-invasive imaging method, produces fine-grained brain images with strong magnetic fields and radio waves. It offers essential knowledge on the physiology, connectivity, and brain organization in people with Parkinson's disease (PD).

a. Structural MRI

Short TE and TR timings are used to create T1-weighted images. The T1 characteristics of tissue mainly control the contrast and brightness of the image. On the other hand, longer TE and TR periods are served to produce T2-weighted images. The T2 characteristics of the tissue dominantly control the contrast and brightness in these images. Typically T1- and T2-weighted images may be identified simply by looking at the CSF. On T1-weighted imaging, CSF is dark, while on T2-weighted imaging, it is bright. The Fluid Attenuated Inversion Recovery (Flair) is a third frequently utilised sequence. The TE and TR timings of the Flair sequence are significantly longer than those of a T2-weighted image. The effect is that the normal CSF fluid is dimmed while anomalies remain bright. This sequence greatly facilitates the distinction between CSF and an abnormality and is highly sensitive to disease.

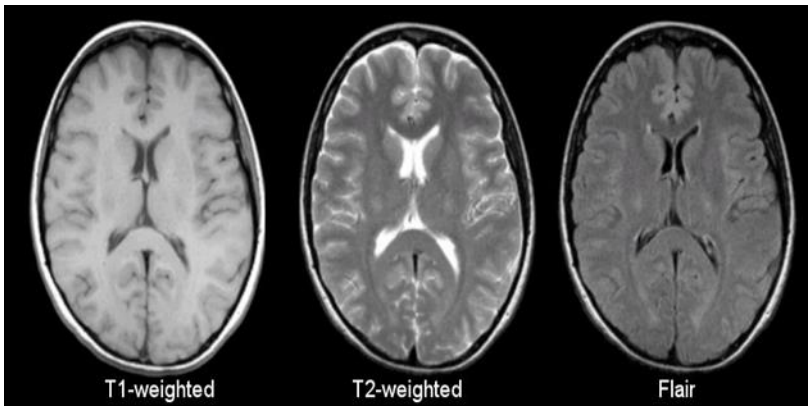

Figure 5: Comparison T1,T2,Flair

T1-weighted MRI scans offer excellent tissue contrast and spatial resolution, allowing for detailed visualization of brain structures. T2-weighted or fluid-attenuated inversion recovery (FLAIR) scans are particularly useful in detecting hyperintensities, white matter abnormalities, or changes associated with neurodegeneration. These structural MRI scans enable the assessment of brain atrophy, the detection of cortical and subcortical changes, and the evaluation of specific brain regions affected in PD.

- T1-weighted MRI : T1-weighted MRI sequences provide excellent tissue contrast, making them ideal for visualizing anatomical structures in the brain. In T1-weighted images, the gray matter appears darker, while the white matter appears brighter. This sequence highlights differences in tissue composition and density. T1-weighted images are commonly used for anatomical assessment, allowing for the detailed visualization of brain structures, such as the cortex, basal ganglia, and ventricles. T1-weighted images are also helpful in measuring brain volume and assessing the presence of atrophy, which can indicate neurodegeneration in PD
- T2-weighted MRI : T2-weighted MRI sequences are susceptible to changes in water content, providing valuable information about tissue pathology and abnormalities. In T2-weighted images, the gray matter appears brighter, while the white matter appears darker compared to T1-weighted images. This sequence helps detect hyperintensities, areas of increased signal intensity, that may indicate pathological changes. In the context of PD, T2-weighted images can help identify white matter abnormalities, visualize changes associated with neurodegeneration, and detect the presence of lesions or other abnormalities in the brain.
- Fluid-Attenuated Inversion Recovery (FLAIR) : FLAIR is a specialized MRI sequence which suppresses cerebrospinal fluid (CSF) signals, providing enhanced

visualization of the brain parenchyma and lesion detection. FLAIR sequences combine a T2-weighted sequence with an inversion recovery pulse, nullifying the CSF signal while preserving the signal from other tissues. This technique improves the detection of hyperintensities by reducing the confounding signal from CSF. FLAIR imaging is advantageous in detecting white matter abnormalities, cortical changes, or lesions associated with neurodegenerative disorders like PD. It allows for better visualization and differentiation of pathology in regions affected by disease-related changes.

By utilizing T1-weighted, T2-weighted, and FLAIR MRI sequences, researchers and clinicians can comprehensively evaluate brain structure, detect abnormalities, and assess changes associated with neurodegenerative processes in PD. These sequences provide valuable information about tissue characteristics, water content, and the presence of hyperintensities or atrophy, participating in a more global understanding of the underlying pathophysiology and progression of the disease.

- Diffusion-Weighted Imaging (DWI) and Diffusion Tensor Imaging (DTI) : DWI analyzes the water molecule diffusion in the brain to reveal information about the white matter tracts' microstructural integrity. DTI is a specific type of DWI that quantifies the directionality of water diffusion, allowing for the reconstruction of white matter fiber tracts and assessment of their connectivity. DWI and DTI techniques have been utilized to study microstructural changes in white matter tracts in PD, revealing alterations in connectivity patterns and providing insights into the underlying pathology.

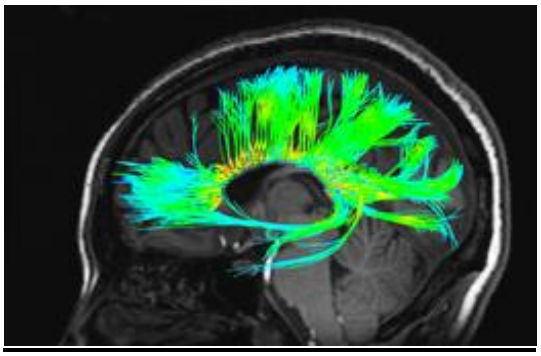

Figure 6: DTI image

- Functional MRI (fMRI): Changes in brain blood oxygenation are measured using fMRI, providing indirect information about neuronal activity and functional connectivity. It enables the study of task-related activations, resting-state networks,

and functional connectivity patterns in individuals with PD. fMRI has been used to investigate motor-related brain activity, cognitive processes, and the impact of PD on functional networks. Resting-state fMRI allows the examination of intrinsic brain activity in the absence of specific tasks, providing insights into functional connectivity disruptions associated with PD.

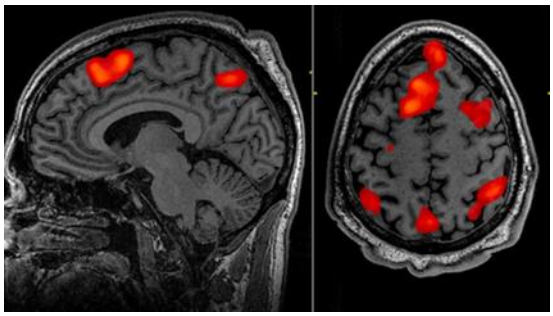

Figure 7: FMRI images

b. Positron Emission Tomography (PET)

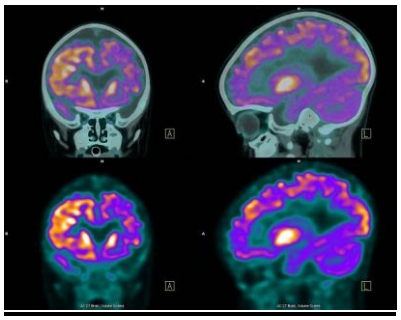

Figure 8: PET Scan

PET imaging involves the injection of radioactive tracers that bind to specific molecules or receptors in the brain. PET scans are commonly used in PD to assess dopamine function by employing radiotracers that bind to dopamine transporters or receptors. In PD patients, reduced dopamine transporter binding is observed in the striatum, particularly the putamen. PET can also be used to study other neurotransmitter systems, such as the serotonin or norepinephrine systems, as well as neuroinflammation or glucose metabolism abnormalities in PD.

c. Single-Photon Emission Computed Tomography (SPECT)

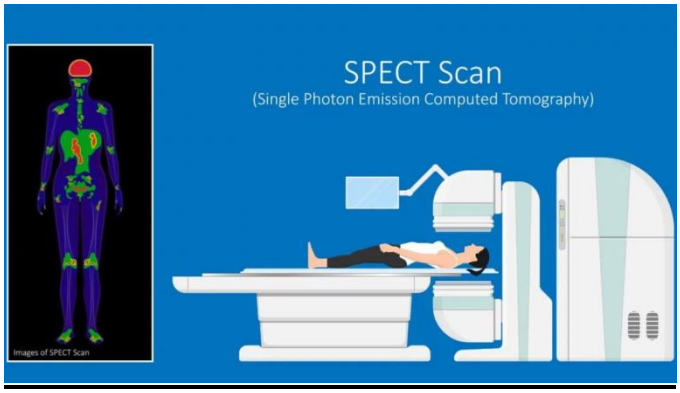

Figure 9: SPECT Scan

SPECT imaging utilizes gamma-ray-emitting radiotracers to measure cerebral blood flow or specific neuroreceptor bindings. SPECT scans can be used in PD to assess dopamine transporter density, similar to PET imaging. SPECT imaging provides functional information about regional cerebral blood flow and can aid in the differentiation of PD from other Parkinsonian disorders

d. Transcranial Doppler (TCD) Ultrasonography

TCD is a non-invasive technique that uses ultrasound waves to measure cerebral blood flow velocities. In PD, TCD can assess blood flow changes in specific brain regions or monitor the response to dopaminergic therapy. TCD can also be used to evaluate the vasomotor reactivity of cerebral vessels, providing insights into cerebrovascular dysfunction in PD.

e. Electroencephalography (EEG) and Magnetoencephalography (MEG)

Non-invasive methods that measure the electrical or magnetic activity of the brain include EEG and MEG. These techniques can assess brain oscillations, event-related potentials, and connectivity patterns in individuals with PD. EEG and MEG offer high temporal resolution and can provide insights into the dynamics of brain activity in PD.

Neuroimaging techniques have significantly contributed to our understanding of PD, allowing for detecting structural and functional changes, the identification of imaging biomarkers, and evaluating therapeutic interventions. These techniques provide valuable tools for researchers and clinicians to study the pathophysiology of PD, monitor disease progression, and develop personalized treatment strategies.

F. Deep learning

Deep learning, a big subset of machine learning, has proven incredibly effective for binary classification problems. Binary classification is a classification with only two possible outcomes, often denoted as 0 and 1 or negative and positive. In Parkinson's Disease, the binary classification could represent the presence or absence of the disease.

The primary use of deep learning is to analyze and interpret medical imaging data, such as MRI or PET scans, which can provide essential insights into the disease progression in Parkinson's patients. Convolutional Neural Networks (CNNs), which is a type of deep learning model, have been particularly effective due to their ability to process images.

Multiple layers of neurons make up CNNs, which can learn to represent incoming data hierarchically. In the case of medical imaging data, the initial layers might learn to recognize simple patterns such as edges or color gradients. In contrast, the deeper layers can learn more complex ways indicative of disease.

Furthermore, deep learning models can also be used to analyze other data relevant to Parkinson's Disease. For instance, Recurrent Neural Networks (RNNs) can be used to analyze time-series data, such as the progression of symptoms over time. This can help clinicians make more accurate predictions about disease progression and optimize treatment plans for individual patients.

Even so, it's critical to remember that while deep learning holds huge opportunity for improving our understanding and treatment of Parkinson's Disease, there are also significant challenges. It begins with the need for large amounts of labeled data to train the models, the difficulty of interpreting the models' decisions, and the risk of overfitting, a situation when the model excels at performing on the training data but fails to generalise to brand-new, untried data.

In conclusion, deep learning provides an exciting and promising avenue for advancing our ability to diagnose and treat Parkinson's Disease. As we continue to refine these models and overcome the associated challenges, we can hope to see significant improvements in patient outcomes.

G. Neural Networks

Machine learning models called neural networks (NNs) are influenced by the biological neural networks seen in animal brains. These networks consist of 'neurons,' or nodes, linked together in a web-like structure. Every connection can carry a signal from one neuron to another, like synapses in a natural brain. The receiving neuron processes the signal and signals downstream neurons connected to it.

In the context of binary classification for Parkinson's Disease, these networks can be trained to distinguish between cases of patients with Parkinson's and those without. The input to the network can be a wide variety of data, such as neuroimaging data, genetic information, patient medical history, etc. If the evidence shows Parkinson's disease is present or not, the output would be a binary decision.

Various NN types can be employed, depending on the data's structure and nature:

1. Feed forward Neural Networks (FNNs)

These Artificial Neural Networks are their most basic variation. Information in this network only moves forward from the input nodes, via any hidden nodes present, and onto the output nodes. The network doesn't contain any loops or cycles.

2. Convolutional Neural Networks (CNNs)

These are mainly employed in image processing, as was previously mentioned. They are made to automatically and adaptively pick up the spatial feature hierarchies from the input.

3. Recurrent Neural Networks (RNNs)

These are used when we require 'memory' of previous inputs in our tasks, such as time-series analysis. They have loops that allow information to be carried across neurons while reading the data, which allows them to remember the context while analyzing a sequence of data.

4. Long Short-Term Memory (LSTM)

A special kind of RNN, LSTM is capable of learning long-term dependencies, which is extremely useful when the network needs to learn from meaningful experiences that have very long time lags in between.

The best neural network architecture to adopt will rely on the particular requirements of the current challenge. Each of these neural network topologies offers advantages and disadvantages. No matter what kind of neural network is utilized, it's critical to remember that they are only tools and that rigorous tweaking and validation are necessary to ensure they produce reliable and accurate predictions.

In Parkinson's Disease, the use of Neural Networks holds great promise in enabling earlier and more accurate diagnosis, which can significantly improve patient outcomes. We expect substantial developments in the field as we collect more data and improve these algorithms.

H. Dicom and Nifti Files Format

1. Dıcom (Digital Imaging and Communications in Medicine)

İs the standard for communicating and managing medical imaging information and related data. It is widely used for storing, sharing, and transmitting information in medical imaging. One of the strengths of DICOM is that it allows the imaging data and the relevant metadata to be stored in one file. This metadata, also known as the DICOM header, can contain a variety of data, including:

a. Patient demographics

This can include data such as the patient's name, ID, age, sex, weight, and other information.

b. Acquisition data

This can include information on how the image was acquired, such as the scanner type, the scanning sequence (for MRI), the voltage and current user (for CT), the scan angle, the number of slices, and other information.

c. Image data

This can include information specific to the image itself, such as the image dimensions, pixel spacing, slice thickness, the orientation of the image, the number of frames, and other data.

This metadata can be very useful in medical imaging analysis. For example:

● Patient demographics can be used in cohort studies to analyze differences in imaging between different groups of patients (e.g., males vs. females, old vs. young).

● Acquisition data can be used to standardize or normalize the images before analysis to account for differences in scanning protocols between scanners or institutions.

● Image data can be used to preprocess the images, such as rescale them to a standard size and orientation.

```
Patient's Name:  DE-IDENTIFIED
Patient's Age:  000Y
Patient's Sex:  F
Modality:  MR
Study Description:  e+1 MR HEAD WITHOUT & WITH CONTRAST
Image Shape:  (256, 256)
```

Figure 10: DICOM Meta Data

2. NIFTI (Neuroimaging Informatics Technology Initiative)

İs a more streamlined format designed explicitly for neuroimaging data. The NIFTI format was developed as a means of increasing the efficiency and effectiveness of neuroimaging data storage, sharing, and analysis.

NIFTI files are simpler than DICOM files and are designed to contain 3D or 4D data arrays. The format includes a header with metadata about the data and the imaging process, followed by the image data. The simplicity of the NIFTI format makes it easier to work with for many researchers, particularly those in the field of neuroimaging.

Both DICOM and NIFTI have their uses in the field of medical imaging. DICOM's extensive metadata and universal application make it a powerful tool for clinical applications, while NIFTI's simplicity and focus on neuroimaging make it an excellent choice for research applications.

These formats can be used to store and process neuroimaging data related to Parkinson's disease. For instance, deep learning models could be trained using DICOM or NIFTI files to find patterns suggestive of the disease. For diagnosis and treatment planning, this could offer helpful information.

It's crucial to remember that using these file formats calls for a solid grasp of both the formats and the underlying image technology. Additionally, it is essential to take precautions to guarantee the ethical and secure handling of patient data.

İ. Transfer learning

Transfer learning is a powerful method in machine learning that allows a model trained on one task to be repurposed on a second related task. In the context of deep learning, A model developed for a study is used on a different task in this process as a starting point for a model.

Transfer learning is beneficial when there's a scarcity of labeled training data. By leveraging models pre-trained on large datasets, we can bootstrap our learning process, which would otherwise require substantial data.

The principle behind transfer learning is that these pre-trained models, often trained on a large-scale image classification task like ImageNet, have already learned robust and generalizable features from the input data. These features can serve as a meaningful and valuable basis for many other studies, including medical imaging tasks such as diagnosing Parkinson's Disease using MRI data.

1. The two main purposes of transfer learning are as follows

a. Feature Extraction

This involves taking the representations learned by a previous network and feeding them into a new classifier (typically a single-layer classifier), which is trained from scratch.

b. Fine-tuning

The basic model is employed as a feature extractor in this case, and its weights are adjusted as well. This is accomplished by carrying on with the training's backpropagation procedure but at a much slower learning pace. As a result, the model can modify its learned features to fit the requirements of the new assignment.

In the context of this study, we're leveraging the power of transfer learning by using DenseNet and ResNet, both of which are pre-trained on ImageNet. These models have already learned to identify a variety of low-level and high-level features from images, and with fine-tuning, they can be adapted to recognize features that are specifically indicative of Parkinson's Disease.

In conclusion, transfer learning is a valuable technique in the toolbox of machine learning practitioners, mainly when dealing with tasks like medical diagnosis where labeled data may be scarce. We can use the strength of extensive pre-training for our particular tasks to stand on the shoulders of giants.

J. DenseNet

Densely Connected Convolutional Networks, or DenseNets, are a type of convolutional neural network (CNN) which has shown significant effectiveness in image classification. DenseNet was introduced by Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger in their paper "Densely Connected Convolutional Networks" in 2016. (33)

The distinguishing feature of DenseNet is the dense connectivity pattern between its layers. In a DenseNet, In a feed-forward connection, each layer learns the feature maps of all layers that came before it and transmit those feature maps to all levels that came after it. In contrast to conventional convolutional networks, which just connect each layer to the next layer.

1. This dense connectivity has several benefits

a. Feature Reuse

Because every layer can access the feature-maps of all preceding layers directly, there is a more efficient use of the features.

b. Improved Flow of Information and Gradients

During training, this dense connection pattern enhances the flow of gradients and information through the network, making DenseNet easier to train and reduces the problem of vanishing gradients.

c. Parameter Efficiency

In comparison to other convolutional networks, DenseNet uses fewer parameters because redundant feature-maps are not necessary to learn.

There are different variants of DenseNet, such as DenseNet-121, DenseNet-169, DenseNet-201, and DenseNet-264. This numbers refer to the total number of layers in the network.

In the context of our thesis on diagnosing Parkinson's Disease using MRI data, a DenseNet can be an effective model. The model can learn to recognize various intricate patterns from the MRI scans that could indicate the disease. Given the model's ability to efficiently use features and its improved flow of information, it can potentially deliver high accuracy in disease detection while using a relatively lower number of parameters.

K. ResNet

ResNet, short for Residual Networks, is a type of convolutional neural network (CNN) architecture that was introduced by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their paper "Deep Residual Learning for Image Recognition" in 2015. The ResNet architecture was developed to solve the problem of training deep neural networks.

Deep neural networks often suffer from a problem known as the "vanishing/exploding gradients" problem. During the training process, as backpropagation computes gradients by continually multiplying derivatives, the gradients can disappear (become infinitesimally small) or explode (become extremely large), making the network hard to train. This problem becomes more pronounced with the increase in the network's depth.

ResNet introduces the concept of a "residual block," which allows it to learn so-called "residual functions" regarding the layer inputs rather than learning unreferenced functions. In practice, this means that in ResNet, each layer retains a residual function concerning the layer inputs, which can be easier to optimize and can help mitigate the vanishing/exploding gradients problem.

A vital component of the ResNet architecture is the "skip connection" (also known as a "shortcut connection"), which allows the gradient to be directly backpropagated to earlier layers. The skip connection performs identity mapping, and its outputs are added to the results of the stacked layers.

ResNet architectures are often very deep, with ResNet variants including ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152, where the numbers denote layers.

In the context of diagnosing Parkinson's Disease using MRI data, ResNet can be a powerful tool. The ability to train intense networks can result in models that can recognize highly complex patterns in the data. It's essential to provide details on how you implemented and used ResNet, including the specific variant, any modifications, the training process, and the model's performance.

L. Monai Framework

Medical Open Network for AI (MONAI): is a PyTorch-based, open-source framework that provides the tools and components needed to create healthcare imaging applications with deep learning. It was designed to create a community-driven, best-of-breed solution for healthcare imaging.

MONAI comes with a host of features that make it suitable for the development and deployment of AI in healthcare:

1. Interoperability with PyTorch

MONAI is designed to work seamlessly with PyTorch, an open-source machine-learning library for Python. This allows developers to leverage the power and flexibility of PyTorch while benefiting from MONAI's specialized tools for medical imaging.

2. Domain-Specific Operations

MONAI provides a wealth of operations specifically designed for medical imaging. These include various transformations (for data augmentation, normalization, etc.), layers (like VNet and UNet), and loss functions (such as Dice loss) that are commonly used in medical image analysis.

3. Flexible Pipelines

MONAI features flexible pipelines for loading, preprocessing, augmenting, and postprocessing medical images. This flexibility allows you to tailor your pipeline to your specific needs.

4. Reproducibility

MONAI places a strong emphasis on enabling reproducible science. It provides capabilities to set and record seeds for random number generators, and tools for experiment tracking.

5. Distributed Training

MONAI supports distributed training, enabling you to train models on multiple GPUs and machines, which can be essential when dealing with significant medical imaging datasets.

In the context of this study on Parkinson's Disease diagnosis using MRI, the MONAI framework provides the following:

- A robust set of tools for loading and preprocessing MRI data.
- Creating and training DenseNet and ResNet models.
- Evaluating their performance.

The domain-specific operations and flexible pipelines offered by MONAI are particularly suited for working with medical imaging data, making it an excellent choice for our project.

IV. TOOLS AND METHODS

A. Data Acquisition and Description

This section will discuss acquiring the MRI data used in this study. An overview of the data source will be supplied, including the collection method, the number of images obtained, and essential information regarding the data structure and format.

1. Data Source

The MRI data utilized in this study were gathered from the Parkinson's Progression Markers Initiative (PPMI). The PPMI is a collaborative research effort involving multiple institutions worldwide to accelerate breakthroughs and treatment advancements in Parkinson's disease. As part of this initiative, an open-access data set and biosample library have been established, providing researchers with valuable resources for investigations related to Parkinson's disease.

2. Data Acquisition

The 3D-T1 MRI data employed in this study consisted of a total of 1,207 images. Specifically, there were 919 MRI scans collected from individuals diagnosed as Parkinson's disease (PD class) and 288 MRI scans from healthy individuals serving as a control group (CN class).

PPMI collected the MRI data using different MRI scanners, including 1.5 Tesla (T) and 3T scanners from multiple vendors. The acquisition protocol followed the standardized protocol developed by the PPMI imaging core, which includes a set of recommended imaging sequences and parameters. The standardized protocol aimed to minimize the variability in data acquisition across different sites and scanners and ensure consistency in data quality.

B. Data Description

Each MRI image in the dataset is stored as DICOM format, which is a standard format commonly used in medical imaging.

The MRI images have varying dimensions and resolutions. The exact dimensions depend on the specific scanning parameters used in the acquisition process. The images typically have X pixels in the sagittal plane, Y pixels in the coronal plane, and Z slices in the axial plane to give an overview. The pixel intensities represent the underlying tissue features recorded by the MRI scanner.

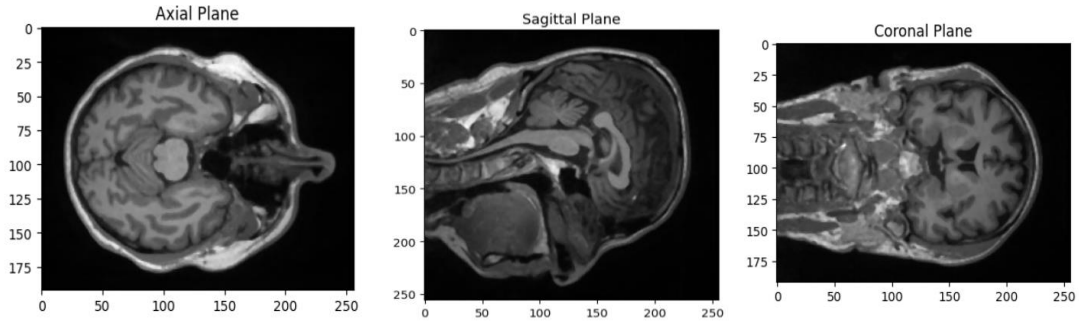

Figure 11: 3D MRI

C. Broad Demographic

The dataset comprises 1,207 images, with 919 MRI scans from individuals with Parkinson's disease and 288 MRI scans from healthy individuals.

The dataset includes a broad demographic, incorporating different age groups, sexes, and research groups. This comprehensive dataset provides the basis for a thorough and diversified analysis.

1. Age Distribution

The dataset's subject population's age distribution was assessed. Ages ranging from 60 to 90 were represented by a diversified histogram plot of the age distribution. The biggest peak in the histogram indicates that the bulk of the subjects are between the ages of 60 and 70.

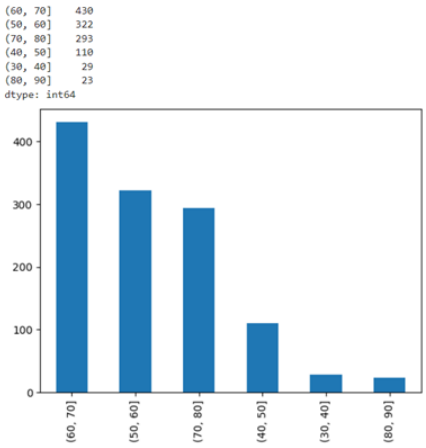

Figure 12: Age Distribution

2. Gender Distribution

The distribution of gender across the dataset was assessed. 32.97% of women and 67.03% of men make up the dataset. This distribution was shown as a bar chart to show the relative proportion of males and females in the dataset.

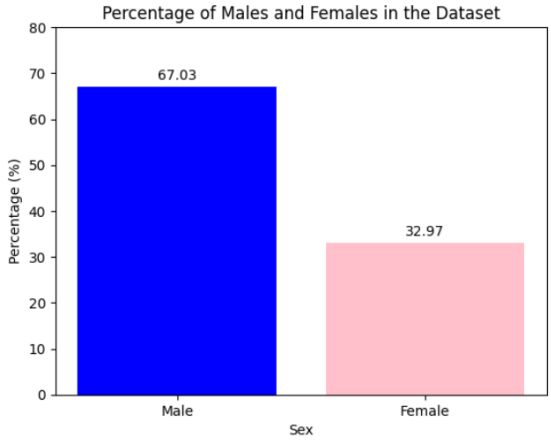

Figure 13: Gender Distribution

3. Research Group Distribution

The dataset contains patients from two different research groups: Control and PD. On a bar graph, numerous subjects in each group were displayed. 919 for PD and 288 for Control.

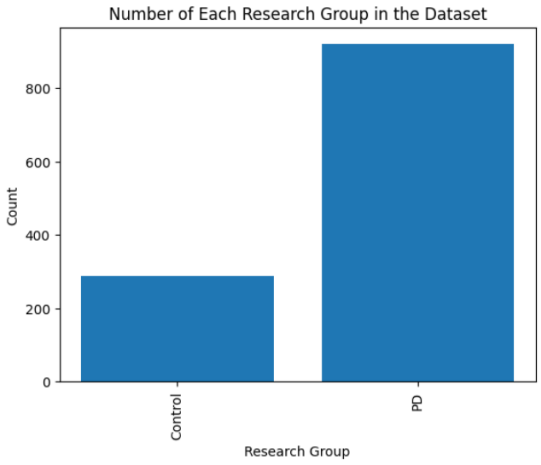

Figure 14: Research Group Distribution

4. Gender Distribution in Each Research Group

Further, each research group's distribution of males and females was also evaluated. In the dataset, 798 subjects were identified as male and 409 as female.

Exciting trends were observed when these totals were broken down by research group.

In the control group, there were 182 males and 106 females. This indicates a more excellent representation of males in the control group, although females were also well represented. In contrast, there were 616 males and 303 females within the PD group. This reveals a significantly more significant representation of males in the PD group.

By conducting a detailed statistical analysis of the dataset, we gained valuable insights into the demographic distribution and representation within the dataset. The diverse age and gender representation, along with a broad range of research groups, underscores the comprehensive nature of the dataset.

Interestingly, the data reveals that the gender distribution is not uniform across the research groups. Males are overrepresented in both groups and particularly so in

the PD group. These insights may have implications for interpreting the results, as gender could be a potential confounding factor.

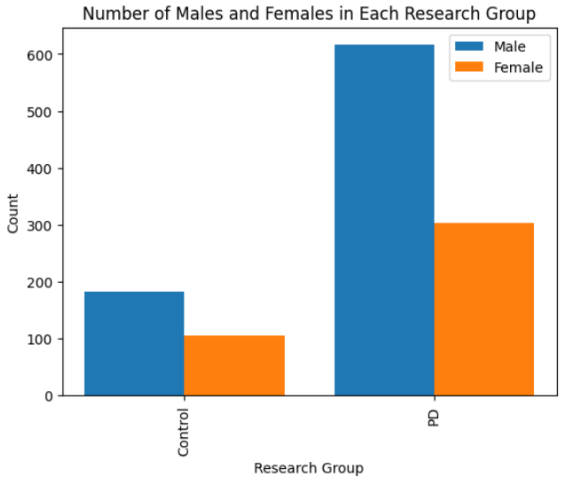

Figure 15: Gender Distribution in Each Research Group

D. Tools and Libraries

Several computational tools and libraries were used for the effective completion of this study, each with its own distinct role and functionality.

1. Numpy

Numpy, short for Numerical Python, was extensively used for handling large, multi-dimensional arrays and matrices of numerical data. It provided high-level mathematical functions necessary for transforming and manipulating our data, making it a key component in our data preprocessing stage.

2. Nibabel

This library was vital for reading and writing access to standard neuroimaging file formats, including NIFTI and ANALYZE. Given the nature of our project, Nibabel was indispensable in handling and transforming the medical imaging data that formed the crux of our research.

3. Nilearn

Nilearn, a library built on top of Scikit-Learn, Nibabel, and Pandas, was utilized for its advanced machine-learning functionalities for neuroimaging data. It offered

valuable features for visualizing neuroimaging volumes and employed machine learning algorithms designed explicitly for neuroimaging.

4. Matplotlib

This library was fundamental to our project for data visualization. Matplotlib's wide range of functionalities allowed us to generate plots, histograms, power spectra, bar charts, error charts, and scatterplots. These were crucial for understanding trends and patterns in our data and visually representing our results.

5. Os

The os library in Python provides functions for interacting with the operating system. This was used in our project for file handling and directory management and to enable interaction between our Python scripts and the system environment.

6. Pydicom

As part of our medical imaging data pipeline, pydicom was instrumental in reading, modifying, and writing DICOM files. This library made it possible for us to access the raw imaging data and the corresponding metadata stored in the DICOM format.

7. Dicom2nifti

To convert DICOM files to NIFTI format, which was more compatible with our data processing and machine learning pipelines, we utilized dicom2nifti. This conversion was essential to interface with several of the other libraries we used, such as Nibabel and Nilearn.

8. Scipy.ndimage.filters

From the SciPy library, we employed the ndimage.filters module for multi-dimensional image processing. These filters performed convolution, correlation, and other image-filtering operations on our medical imaging data.

9. BrainExtractor

The BrainExtractor tool was crucial in our preprocessing pipeline, enabling us to perform brain extraction in the given neuroimages. This step was vital for reducing the dimensionality of the data and focusing on relevant regions for analysis.

10. PyTorch

PyTorch was the primary machine-learning library used in our project. It's flexibility and intuitive interface facilitated the design, training, and testing of deep learning models. PyTorch's dynamic computational graph allowed us to effectively visualize the learning process and adjust our model's behavior dynamically, which was crucial for optimizing our model's performance.

11. Ignite

Ignite is a powerful library built on top of PyTorch that dramatically simplifies neural networks' training and evaluation process. With its intuitive API and extensive set of utilities, Ignite allows researchers and practitioners to focus on the core aspects of their binary classification tasks for Parkinson's Disease using MRI data. Ignite handles repetitive boilerplate code by providing a high-level training loop abstraction, such as handling data loading, managing model parameters, and reporting metrics. This improves code organization and readability and enables efficient experimentation and iteration on model architectures, hyperparameters, and optimization strategies.

12. TensorBoard

TensorBoard, a web-based visualization tool offered by TensorFlow, is an invaluable companion for analyzing and monitoring the performance of binary classification models for Parkinson's Disease using MRI data. With TensorBoard, researchers can effortlessly gain insights into the training process and make informed decisions. By visualizing training and validation loss curves, accuracy trends, and other relevant metrics, TensorBoard provides a comprehensive view of the model's behavior over time. Moreover, TensorBoard's capability to display histograms of weights and biases allows researchers to observe the distribution of learned parameters, aiding in diagnosing potential issues such as vanishing or exploding gradients. With its interactive and user-friendly interface, TensorBoard empowers researchers to optimize their models effectively and accelerate the development of accurate classification algorithms.

The particular functionality, thorough documentation, and active community support of these tools and libraries were factors in their selection. These factors significantly sped up the development and troubleshooting processes.

V. SYSTEM OVERVIEW AND DESIGN

A. Work Flow

The project workflow is designed to be sequential yet flexible, allowing for revisions and refinements at each stage based on the observations and results obtained. The following is a step-by-step breakdown of the workflow:

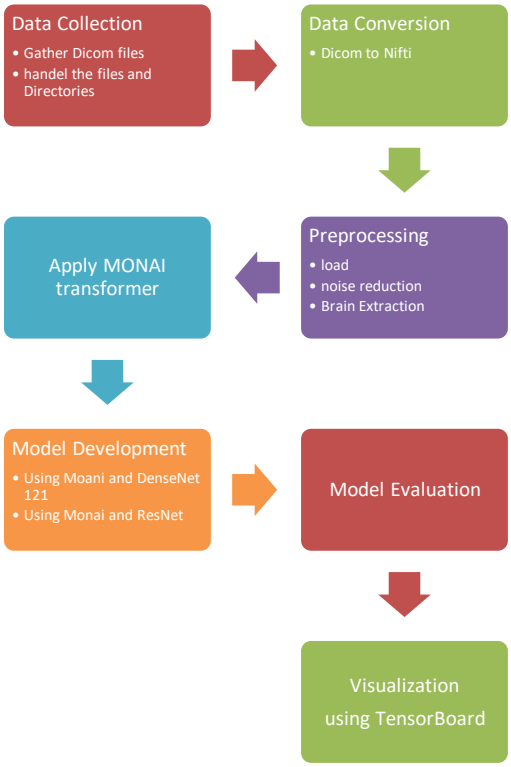

Figure 16: Work Flow

1. Data Collection

Gather the required DICOM files from PPMI, and Utilize the os library for file handling and directory management

2. Data Conversion

Convert DICOM files to NIFTI format using the dicom2nifti tool for enhanced compatibility with other libraries.

3. Data Pre-processing

Load and handle the NIFTI files using the Nibabel library and visualize 3D and 2D images.

4. Data Visualization

In this step, we visualize the neuroimaging data to better understand its structure and to identify any obvious issues or anomalies.

a. 3D visualization

This is performed using the Nilearn library in Python, which is specifically designed for neuroimaging data analysis.

```
[ ] from nilearn import plotting

    plotting.plot_img(nifti_file)
    #This will display a 3D image of your NIfTI file.

    <nilearn.plotting.displays._slicers.OrthoSlicer at 0x7eff09b59610>
```

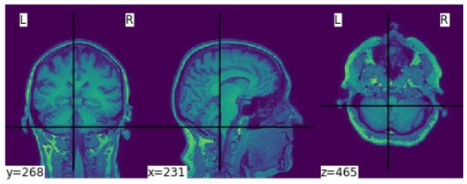

Figure 17: 3D Visualization

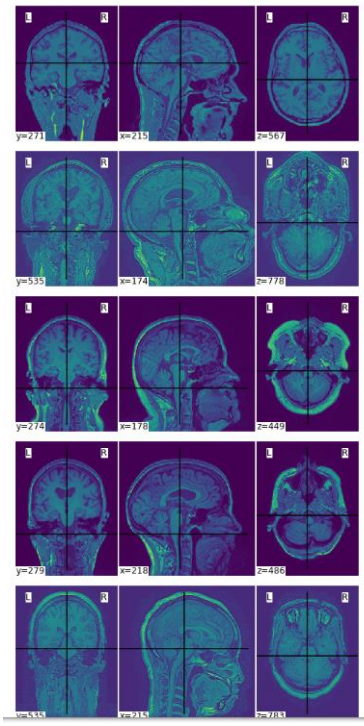

Figure 18: 3D visualization for multiple nifti files

b. 2D visualization

Using Matplotlib is a powerful and flexible Python library for creating static, animated, and interactive visualizations.

Figure 19: 2D Visualization

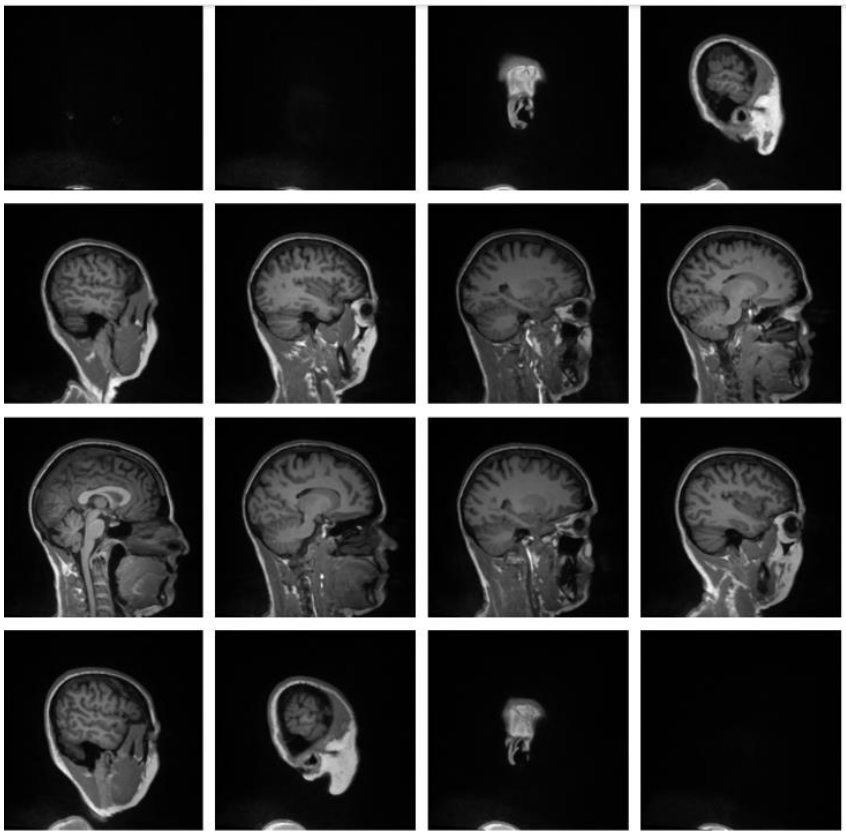

Figure 20: Series of slices

5. Apply Noise Reduction Filters Using the ‘scipy.ndimage.filters’ Modüle

To process the neuroimaging data, we use a Python script that applies a median filter to each NIfTI file in the input directory. The median filter is used to reduce noise and smooth the image.

The script starts by setting the paths to the input and output directories. It then iterates over each file in the input directory, loading NIfTI files using 'NiBabel's' load function and the 'get_fdata' method to extract the data.

The 'median_filter' function from the 'scipy.ndimage.filters' library is then used to apply a median filter to the data. The size parameter is set to 3, indicating that the filter should consider a 3x3x3 neighborhood around each voxel (3D pixel) to calculate the median value.

After the median filter is applied, a new NIfTI file is created with the filtered data using the 'Nifti1Image' constructor from 'NiBabel'. The header information and the affine transformation matrix (which defines the relationship between the voxel coordinates and the world coordinates) from the original file are used to construct the new file.

Finally, the new NIfTI file is saved in the output directory with the same filename as the original file. This is done using NiBabel's save function.

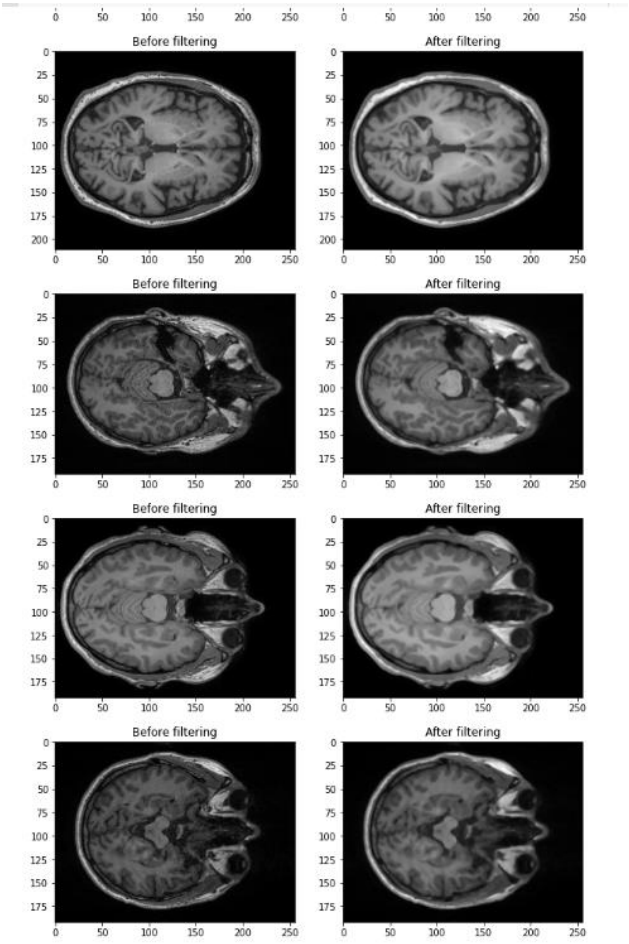

Figure 21: Noise reduction Before and After

6. Execute brain extraction

İn the neuroimages with the BrainExtractor tool to focus on relevant regions for analysis and reduce data dimensionality.

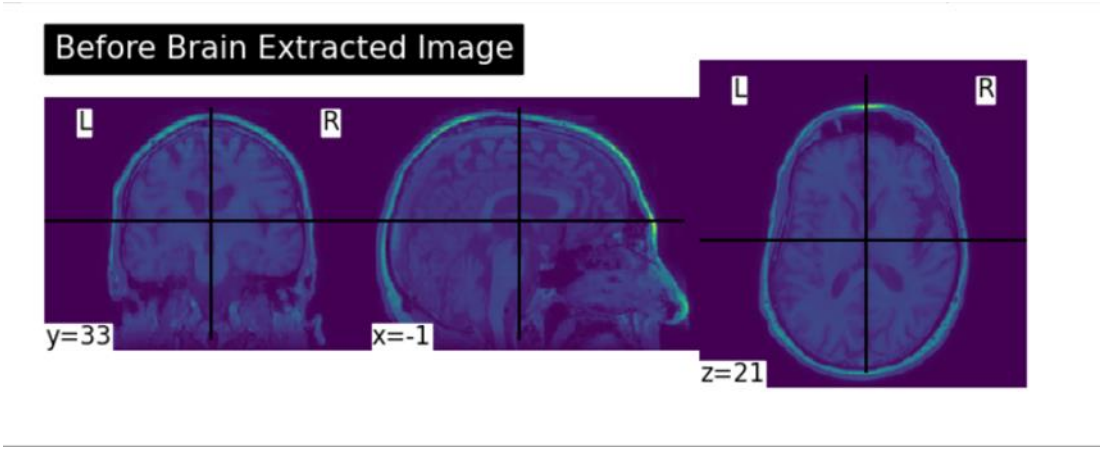

Figure 22: Before Brain Extraction

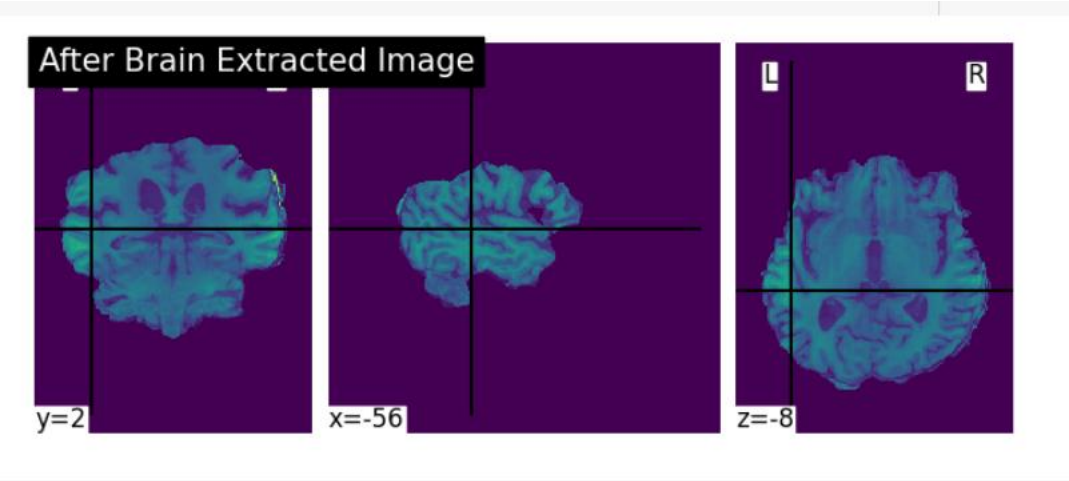

Figure 23: After Brain Extraction

7. Data Augmentation for 'class CN'

Because of the less number of images in class 'CN' we make Data Augmentation using MONAI Transformation and generate new images after augmentations and save them to reuse this images in the training steps.

a. Rotate90()

This transformation rotates the input image by 90 degrees. It can introduce variations by changing the orientation of the image.

b. Flip()

This transformation horizontally flips the input image. It can simulate mirror images and introduce left-right variations.

c. EnsureType()

This transformation ensures that the output image has the desired data type. It can be useful for maintaining consistency in the data type across transformations.

d. Transforms.RandFlip()

This transformation randomly flips the input image horizontally or vertically. It introduces randomness and further diversifies the data.

e. Transforms.RandRotate()

This transformation randomly rotates the input image within a certain range. It adds variability by changing the orientation at random angles.

f. Transforms.RandZoom(min_zoom=0.9, max_zoom=1.1)

This transformation randomly applies zooming to the input image within the specified zoom range. It can simulate different scales and perspectives.

By applying these augmentations to Class ‘CN’ samples only, this can introduce variations and generate additional training samples specific to that class. This helps to improve the model's ability to learn diverse representations and make accurate predictions.

VI. MODEL IMPLEMENTATION, TRAINING AND EVALUATION

A. Introduction

Binary classification for Parkinson's Disease (PD) using Convolutional Neural Networks (CNNs) and Transfer Learning algorithms have gained significant attention in medical imaging analysis. Parkinson's Disease is a neurodegenerative disorder affecting millions worldwide, and early and accurate diagnosis is crucial for effective treatment and management. In recent years, deep learning techniques, specifically CNNs, have shown promising results in automating the diagnosis process based on medical imaging data, such as Magnetic Resonance Imaging (MRI).

This section focuses on implementing, training, and evaluating CNN-based models for the binary classification of PD using MRI data. Specifically, two popular CNN architectures, DenseNet121 and ResNet, are utilized in this study. These architectures have demonstrated strong performance in various computer vision tasks, including medical image analysis.

The MONAI (Medical Open Network for AI) architecture is employed to simplify the implementation and training process. A domain-specific open-source framework called MONAI was created to hasten to make and apply deep learning models in medical imaging. It offers many preprocessing transformations, data management tools, and evaluation measures designed specifically for medical imaging jobs.

Transfer Learning, a powerful technique in deep learning, is also explored in this chapter. The models can capture rich and abstract image features by leveraging pre-trained models, such as DenseNet121 and ResNet, trained on large-scale datasets like ImageNet. Transfer Learning allows the models to be fine-tuned on the specific task of PD classification with limited labeled medical imaging data. This approach reduces the computational burden and enhances the model's generalization capabilities.

The data preprocessing includes intensity normalization, resizing, and augmentation techniques such as rotation, flipping, and random transformations. These preprocessing techniques ensure the input data is standardized and contains sufficient variability for the models to learn meaningful patterns and generalize well.

The training process involves iteratively feeding the preprocessed data into the DenseNet121 and ResNet models and updating their parameters to minimize classification loss. The models are trained using a labeled dataset of MRI scans from PD patients and healthy controls. The training progress is monitored by tracking the loss function and validation accuracy. Early stopping techniques may be employed to prevent overfitting and determine the optimal number of epochs.

Evaluation metrics such as accuracy and F1-score assess the models' classification performance.

By implementing and training DenseNet121 and ResNet models using the MONAI framework, this section aims to comprehensively understand their performance for binary classification of PD using MRI data. The results and analysis obtained from this study can contribute to developing accurate and reliable tools for the early recognition and diagnosis of Parkinson's Disease.

B. Software Environment

Figure 24: Software Enviroment

By using the MONAI library configuration monai.config.print_config(), which provides an overview of the versions and dependencies of the MONAI library used in the implementation.

The MONAI library version 1.1.0 is utilized, which indicates the specific release of the library used for developing the AI module. This information is significant for reproducibility and ensuring that the code is compatible with the expected MONAI functionalities.

The output also lists optional dependencies that are used alongside MONAI. These dependencies include

1. PyTorch Ignite version 0.4.12

Ignite is a high-level library built on top of PyTorch for simplifying the process of creating trainers, evaluators, and handlers for deep learning models.

2. Nibabel version 3.0.2

Nibabel is a Python library for reading and writing neuroimaging file formats, including the NIfTI format used in this implementation.

3. Scikit-image version 0.19.3

Scikit-image is a library for image processing in Python. It provides various image manipulation and analysis functions.

4. Pillow version 8.4.0

Pillow is a fork of the Python Imaging Library (PIL) and provides image processing capabilities.

5. Tensorboard version 2.12.2

TensorBoard is a visualization tool provided by TensorFlow for monitoring and analyzing training runs

6. Gdown version 4.6.6

Gdown is a library for downloading files from Google Drive using their file IDs.

7. TorchVision version 0.15.2+cu118

TorchVision is a package in PyTorch that provides pre-trained models, datasets, and transformations for computer vision tasks.

8. Tqdm version 4.65.0

Tqdm is a library for adding progress bars to Python loops.

9. Additionally

Additionally, the output mentions the versions of other optional dependencies, such as lmdb, psutil, pandas, einops, transformers, mlflow, and pynrrd. These dependencies might not be installed or their versions are not known.

C. Load the dataset and split it

This segment is responsible for preparing the dataset for training and validation. Here's a description:

1. Two paths are defined to specify the directories containing the training and validation datasets, respectively.

2. The **os.listdir()** function is used to obtain a list of filenames within the training directory. The list is then sorted in ascending order.

3. Empty lists are initialized to store the image paths and corresponding labels for the training and validation sets, as well as combined lists for all images and labels.

4. A loop iterates over the filenames in the training dataset. If a filename starts with 'PD', it indicates a sample with Parkinson's Disease, and the label: ‘1’ is appended to both **tr_labels** and **labels** lists. Otherwise, a label of ‘0’ is appended to both lists.

5. The file path is created by joining the training directory path with the current filename using **os.path.join().**

6. The **nib.load()** function is used to load the image data from the file path, and the path is appended to **tr_images** and **images** lists for future reference.

7. Information about the loaded image, including the file path and shape, is printed.

8. The **tr_labels** list is converted into a **NumPy** array using np.array(), with the data type set to **np.int64**.

9. A similar process is performed for the validation dataset. Filenames are obtained using **os.listdir()** on the validation directory, sorted, and iterated over. **Labels** are appended to the labels and **val_labels** lists based on the prefix **'PD'** in the filenames. Image paths are added to the images and **val_images** lists, and information about the loaded images is printed.

10. Finally, the **labels** list is converted to a **NumPy** array with the data type set to **np.int64.**

Overall, the segment loads the dataset, assigns appropriate labels to the images based on their filenames, stores the file paths and labels in separate lists, and converts the labels to NumPy arrays for further processing in the model implementation and evaluation phases.

D. Define Transformers, Datasets and DataLoaders

This part is responsible for defining the transformers, datasets, and data loaders for the training and validation sets. Here's the description:

1. Two sets of transforms are defined: train_transforms and val_transforms.

a. Train_transforms is a composition of transformations including ScaleIntensity() for scaling the image intensities, EnsureChannelFirst() for reordering the image channels, Resize() to resize the images to a specified shape of (96, 96, 96), and RandRotate90() for randomly rotating the images by 90 degrees.

b. Val_transforms is a composition of transformations similar to train_transforms, excluding the RandRotate90() transformation.

2. A dataset **(check_ds)** and a data loader **(check_loader)** are created for checking the first batch of the dataset.

a. The **ImageDataset** is initialized with **image_files** (the list of all image paths) and labels (the list of all corresponding labels) from the combined dataset. The specified transform parameter is **train_transforms.**

b. The **DataLoader** is initialized with **check_ds** and configured with a batch size of 16, 2 worker processes for data loading, and memory pinning if **CUDA** is available.

c. **Monai.utils.misc.first()** is used to retrieve the first batch of data from the data loader.

d. Information about the type and shape of the image tensor (im) and the label tensor **(label)** is printed.

3. A dataset **(train_ds)** and a data loader **(train_loader)** are created for the training set.

a. The **ImageDataset** is initialized with **image_files** (the list of training image paths) and labels (the list of training labels). The specified transform parameter **is train_transforms.**

b. The **DataLoader** is initialized with **train_ds** and configured with a **batch** size of **16**, shuffling the data, 2 worker processes for data loading, and memory pinning if CUDA is available

3. A dataset **(val_ds)** and a data loader **(val_loader)** are created for the validation set.

a. The **ImageDataset** is initialized with **image_files** (the list of validation image paths) and labels (the list of validation labels). The specified transform parameter is **val_transforms.**
b. The **DataLoader** is initialized with **val_ds** and configured with a batch size of 16, 2 worker processes for data loading, and memory pinning if CUDA is available.

These transformers, datasets, and data loaders are essential for preprocessing and organizing the image data for model training and evaluation. The transformers apply specific operations to the images, the datasets encapsulate the image paths and labels, and the data loaders provide an interface to efficiently load the data in batches during training and validation.

E. Model Architecture

1. ResNet

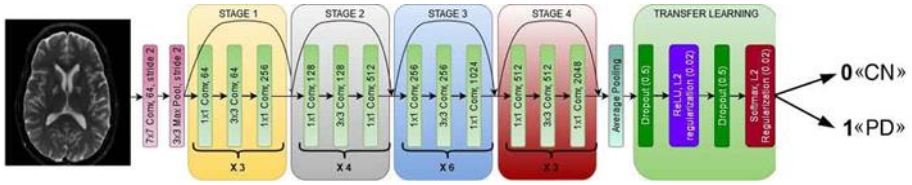

Figure 25: ResNet Model

The model used is a variant of the ResNet (Residual Network) architecture, specifically designed for 3D image classification tasks. Here are more details about the model:

a. Architecture

The ResNet architecture is a deep convolutional neural network that addresses the problem of vanishing gradients in deep networks by introducing skip connections or residual connections. This helps in alleviating the degradation problem, allowing the network to be deeper while maintaining performance.

b. Basic ResNet

The ResNet variant used in the code is referred to as "basic". It consists of four stages, each containing multiple residual blocks. The number of residual blocks in each stage is defined by the layers parameter. In this case, the layers list is set to [1, 1, 1, 1], indicating one residual block in each stage.

c. Block Inplanes

The **'block_inplanes'** parameter specifies the number of input planes (channels) for each residual block in the respective stages. In the model, the **'block_inplanes'** list is set to [64, 128, 256, 512], indicating the number of input channels for the four stages, respectively.

d. Spatial Dimensions: The 'spatial_dims'

The **'spatial_dims'** parameter defines the spatial dimensions of the input data. In this case, it is set to 3, indicating that the input data is 3D volumetric data.

e. Input Channels

The **'n_input_channels'** parameter specifies the number of input channels in the input data. In the code, it is set to 1, indicating grayscale images.

f. Number of Classes

The **'num_classes'** parameter specifies the number of output classes that the model needs to predict. In this case, it is set to 2, representing the **binary classification** task of distinguishing between individuals with PD and healthy controls.

By instantiating this ResNet model, the code sets up a deep neural network architecture capable of processing 3D MRI data and performing binary classification

for Parkinson's Disease. The model is then moved to the specified device (GPU if available) for computation.

2. DenseNet121

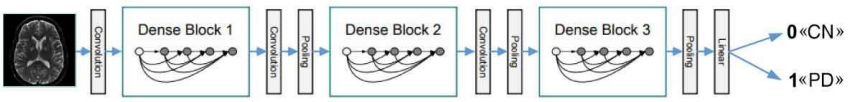

Figure 26: DenseNet121 Model

a. The model used in the code snippet is DenseNet121. It is a variant of the DenseNet architecture, specifically designed for 3D image analysis. DenseNet architectures have gained popularity due to their effectiveness in capturing intricate patterns and features from images.

b. The **DenseNet121** model consists of **121 layers**, making it a relatively deep network. It is specifically designed for spatial dimensions of 3, which indicates that it is suitable for processing 3D volumetric data, such as MRI scans. In the context of Parkinson's Disease classification using MRI data, this is particularly relevant as it allows the model to analyze the volumetric information present in the images.

c. The input to the DenseNet121 model is an MRI image with a single channel. The "in_channels" parameter is set to 1, indicating that the model expects input images with a single channel representing the intensity values. This is typical for **grayscale** images such as MRI scans.

d. The output of the DenseNet121 model is a 2-channel output, represented by the **"out_channels"** parameter set to 2. This means that the model predicts the probability distribution over two classes: PD and healthy controls. The model learns to assign a probability to each class based on the learned features extracted from the input MRI images.

e. By setting the model to the **"device"** specified (e.g., **"cuda"** for GPU or **"cpu"** for CPU), the computations and operations of the DenseNet121 model will be performed on the selected device, ensuring efficient processing and utilization of available resources.

Overall, the DenseNet121 model is a deep learning architecture specifically designed for 3D image analysis. It is utilized in this context for binary classification of Parkinson's Disease using MRI data. The model takes advantage of its depth and dense connectivity to extract meaningful features from the input images, enabling accurate classification and diagnosis.

F. Loss Function

The loss function used is CrossEntropyLoss. It is a commonly used loss function for multi-class classification tasks, including binary classification as a special case.

The CrossEntropyLoss function combines both the softmax activation and the negative log likelihood loss in a single operation. It encourages the model to assign high probabilities to the correct class and low probabilities to the incorrect class.

In the specific context of Parkinson's Disease classification, the model's output is a probability distribution over the two classes: PD and healthy controls. The CrossEntropyLoss function takes this probability distribution and the corresponding ground truth labels as inputs. It computes the loss by comparing the predicted probabilities with the true labels, taking into account both the correct and incorrect predictions.

The use of CrossEntropyLoss as the loss function is appropriate for training the model to optimize the parameters based on minimizing the classification error. By minimizing the loss, the model learns to improve its predictions and make more accurate classifications.

The use of CrossEntropyLoss as the loss function is appropriate for training the model to optimize the parameters based on minimizing the classification error. By minimizing the loss, the model learns to improve its predictions and make more accurate classifications.

G. Optimizer

The optimizer used is Adam. The Adam optimizer is instantiated with the model's parameters as the input. By passing ‘model.parameters()’as an argument, the

optimizer is aware of the model's learnable parameters (weights and biases) that need to be updated.

The learning rate, specified as 1e-5, determines the step size at which the optimizer adjusts the model's parameters during each update. A smaller learning rate typically leads to slower but more precise convergence, while a larger learning rate may result in faster convergence but with the risk of overshooting the optimal solution.

H. Training

1. Before the training process is begin, we indicate the validation step to be performed every 2 epochs, and the best metric value obtained during training initialized to -1, this will be used to track the best metrics through the training process. And 'SummaryWriter' is used to visualize and log the training process. The maximum number of epochs is set to 100. Early stopping technique was used. Two empty lists, 'epoch_loss_values' and 'metric_values', are created to store the epoch-wise loss values and metrics, respectively.

2. Then the training loop begins with a loop over each epoch. Within each epoch, the model is set to training mode. And epoch loss is initialized to 0 to calculate the average loss for the current epoch. A step variable is introduced to track the progress within the epoch.

3. The loop iterates over the batches of data in the train loader. After completing the epoch, the average loss is calculated.

4. Then the model is set to evaluation mode. Where the validation loop is performed if the current epoch number plus one is divisible by validation interval. The loop iterates over the batches of data in the validation loader.

In this process we implement the training loop for a model using the MONAI framework. Performs forward and backward passes, updates the model's parameters using the Adam optimizer, and tracks the training and validation metrics. The training process continues for a maximum number of epochs while monitoring the validation metric for potential early stopping.

İ. Result And Discussion

The Accuracy and F1 score were calculated as evaluation metrics for the model performance, comparing the two results for two models (ResNet and DenseNet121) and decides which the best is.

```
  warnings.warn(f"Modifying image pixdim from {pixdim} t
/usr/local/lib/python3.10/dist-packages/monai/data/utils
  warnings.warn(f"Modifying image pixdim from {pixdim} t
Accuracy: 0.9250
F1 score: 0.9247
```

Figure 27: ResNet result

- **Accuracy: 0.9250**
- **F1 Score: 0.9247**

The ResNet model achieved an accuracy of 0.9250, indicating that it correctly classified 92.50% of the instances in the validation set. The F1 score of 0.9247 suggests a balanced performance in terms of precision and recall.

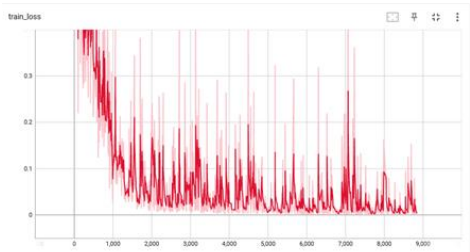

Figure 28ResNet Validation accuracy Figure 29: ResNet train loss

J. DenseNet121

```
  warnings.warn(f"Modifying
Accuracy: 0.8850
F1 score: 0.8847
```

Figure 30: DenseNet121 result

- Accuracy: 0.8850
- F1 Score: 0.8847

The DenseNet121 model achieved an accuracy of 0.8850, correctly classifying 88.50% of the instances in the validation set. The F1 score of 0.8847 indicates a balanced performance between precision and recall.

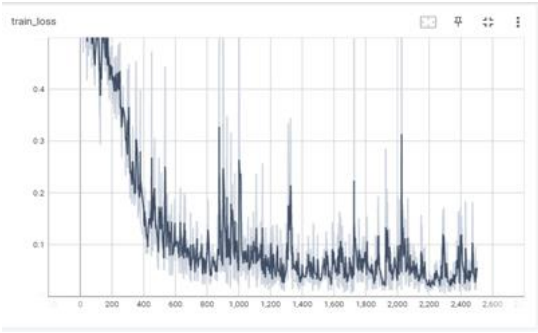

Figure 31: DenseNet121 train loss

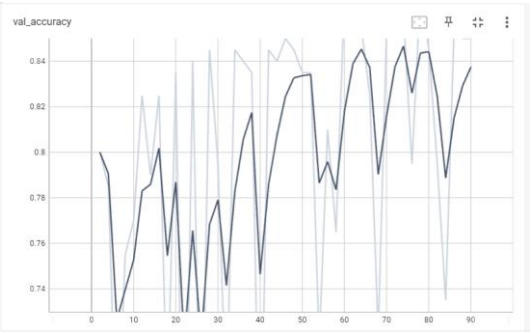

Figure 32: DenseNet121 validation accuracy

1. Comparing the two models

1. The ResNet model outperformed the DenseNet121 model in terms of accuracy, achieving a higher accuracy of 0.9250 compared to 0.8850 for DenseNet121.

2. The F1 score for ResNet (0.9247) is slightly higher than DenseNet121 (0.8847), indicating that the ResNet model achieved a better balance between precision and recall.

It is important to note that these results are specific to the dataset and problem at hand. The ResNet model demonstrates a superior ability to classify Parkinson's disease based on MRI Nifti files compared to DenseNet121.

2. Further analysis and discussion based on the points you mentioned

a. Interpretation of Accuracy and F1 Scores

a. The accuracy and F1 scores provide an evaluation of the model's performance in classifying Parkinson's Disease from MRI Nifti files.

b. A high accuracy (0.9250 for ResNet) indicates that the model can correctly identify Parkinson's Disease cases, which is crucial for early diagnosis.

c. The F1 score (0.9247 for ResNet) considers both precision and recall, providing a balanced measure of the model's ability to classify both Parkinson's Disease and non-Parkinson's Disease cases.

d. These scores demonstrate the potential of the model to aid in the early detection of Parkinson's Disease, allowing for timely intervention and treatment.

b. Reasons for Superior Performance of ResNet

a. ResNet's deeper architecture and skip connections contribute to its superior performance.

b. Deeper architectures enable the model to learn more complex patterns and capture finer details from the MRI images.

c. Skip connections allow for better gradient flow during training, alleviating the vanishing gradient problem and facilitating the optimization process.

d. The combination of these factors enables ResNet to extract and leverage meaningful features for accurate classification, leading to its superior performance compared to DenseNet121.

VII. CONCLUSION

Parkinson's Disease (PD) is a neurodegenerative disorder characterized by motor symptoms such as tremors, bradykinesia, and rigidity. So an early and accurate diagnosis of this disease is crucial for effective treatment and management of the disease. The disease is diagnosed using many different ways, and the most important prominent and most accurate of which is Magnetic Resonance Imaging (MRI) has emerged as a promising modality for analysing brain structures and detecting neurodegenerative diseases.

Using MRI, This study has implemented two binary classification models to distinguish between individuals with PD and healthy controls. By employing PyTorch, and MONAI to design, implement, and training of deep learning models. Transfer learning Techniques also used to implement DenseNet121 and ResNet architectures, leveraging their proven effectiveness in image classification tasks.

While this study achieved high accuracy and F1 score, ResNet outperformed DenseNet121, reaching an accuracy of 0.9250 and F1 Score of 0.9247, where the accuracy in DenseNet was 0.8850 and F1 score 0.8847. This result showcases the efficacy of ResNet in PD classification tasks. The results of this work advance the use of MRI and deep learning methods for PD diagnosis. We think that these discoveries could lead to useful clinical applications that would ultimately help those who have Parkinson's disease and facilitate early diagnosis and treatment.

Looking forward, we plan to expand our research by exploring different model architectures: Apart from ResNet and DenseNet, like Inception, VGG, or EfficientNet to identify the most suitable architecture for Parkinson's Disease classification. Additionally we will incorporate various data augmentation techniques such as translations, or elastic deformations, which could enhance the models' ability to generalize to unseen variations in the MRI images. And to perform better and improve model performance and generalization skills, we may give our models more varied examples to learn from by expanding the training dataset, which may.

By the end of this work, we are hopeful that further investigation and study in this field will advance the diagnosis and treatment of Parkinson's disease, bringing us closer to better patient outcomes and higher standards of living.

VIII. REFERENCES

Journals:

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RESUME

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Python – Machine Learning – Deep learning – Computer Vision- CNN- Numpy- Pandas- Matplotlib- PyTorch

Education

March 2010: Computer Engineer, ISLAMIC UNIVERSITY OF GAZA – PALESTINE

OCTOBER 2023: Artificial intelligence and data science, Istanbul aydin university-Turkey

Skills

- Data Scientist
- Experience in Pyton
- TensorFlow Developer.
- Machine learning algorithms Supervised, Unsupervised and Rainforcement. (Regression, Neural Networks, Decision Trees such as (LightGBM, XGBoost).
- Convolutional Neural Networks in TensorFlow
- Natural Language Processing, Computer Vision, Data classification, and Data Augmentation, Image Segmentation.
- Experience with standard libraries in ML pipelines such as (NumPy, SciPy, Pandas, PySpark, SciKit-Learn, TensorFlow/PyTorch, NLTK, GenSim, OpenCV, MatPlotLib).
- Familiarity with relational/non-relational databases, application development frameworks, and POSIX-based systems.

- Advanced SQL and query performance tuning skills

Quality Management Experience

- ISO9001
- EFQM
- Seven Quality Tools
- Quality Control
- MiniTab
- Visio

Architecture and Software Design

- Software Development Life Cycle (SDLC)
- Object Oriented Programming
- System Modelling

Software Testing

- Strong debugging, coding, and analytical problem solving skills
- Software Testing Methodologies
- Manual Testing (Test Cases, Test Scenario, Bug Report ‘Jira’)
- Automation Testing. (Selenium)
- Strong root-cause analysis skills
- Document test cases and test coverage
- Perform and document risk analysis
- Record test progress and results,
- Create test plans.

Database

- MYSQL
- ORACLE

Programming Language

- Python
- Java
- Php

Languages

- Arabic
- English

Personal Skills

- Strong creative & innovative ability
- Leadership
- Team working
- Accuracy
- Learning agility
- Well versed with the computer languages & the basic concepts

Certifications

ISTQB CTFL Certificate No: 0722 CTFL34972022