Detection of Parkinson's Disease from Neuro-imagery using Deep Neural Network with Transfer Learning

by

Asaduzzaman
17101531
A.F.M. Nazmus Sakib
16201005
Sanjida Ali Shusmita
16301154
S. M. Ashraf Kabir
16301034

A thesis submitted to the Department of Computer Science and Engineering
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B.Sc. in Computer Science

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Brac University
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Declaration

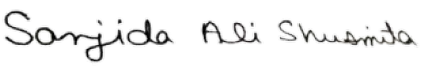
It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

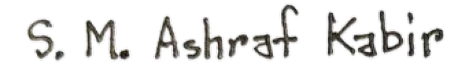
Student's Full Name & Signature:

Asaduzzaman
17101531

A.F.M. Nazmus Sakib
16201005



Sanjida Ali Shusmita
16301154



S.M. Ashraf Kabir
16301034

Approval

The thesis titled "Detection of Parkinson's Disease from Neuro-imagery Using Deep Neural Network With Trnsfer Learning" submitted by

1. Asaduzzaman (17101531)
2. A. F. M. Nazmus Sakib (16201005)
3. Sanjida Ali Shusmita (16301154)
4. S. M. Ashraf Kabir (16301034)

Of Spring, 2020 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of B.Sc. in Computer Science and Engineering on April 07, 2020.

Examining Committee:

Supervisor:
(Member)

Zavid Parvez Digitally signed by Zavid Parvez
DN: cn=Zavid Parvez, o=Brac University, ou=CSE, email=zavid.parvez@bracu.ac.bd, c=US
Date: 2020.07.04 15:43:59 +06'00'

Mohammad Zavid Parvez,PhD
Assistant Professor
Department of Computer Science and Engineering
Brac University

Co-Supervisor:
(member)

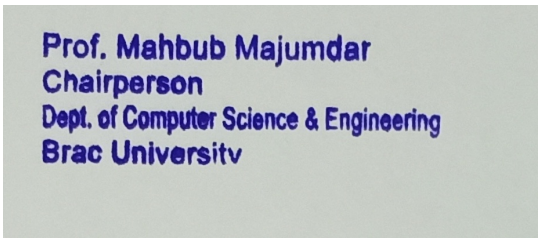
Tanzim 6.7.2020

Md. Tanzim Reza
Lecturer
Department of Computer Science and Engineering
Brac University

Thesis Coordinator:

Dr. Md. Golam RabiulAlam
Associate Professor
Department of Computer Science and Engineering
Brac University

Head of Department:
(Chair)



Mahbubul Alam Majumdar,PhD
Professor and Charperson(CSE)
Department of Computer Science and Engineering
Brac University

Abstract

Parkinson's disease is a neurological condition that is dynamic and steadily influences the movement of the human body. It causes issues within the brain and slowly increments time by time. Tremor is the major side effect of PD where the entire body begins shaking. Besides, a person's muscle may end up rigid or stiff and it may happen any portion of his body. PD influences the central apprehensive system which is happening because of the hardship of dopaminergic neurons brought about in a neuro-degenerative incubation. It is grouped beneath advancement clutter as patients who have PD appear with tremor, unyielding nature, postural shifts, and lessen in unconstrained advancements. There is no particular diagnosis process for PD. PD varies from one person to another person and the situation and history. MRI, CT, ultrasound of the brain, PET scans are common imaging tests to figure out this disease but these tests are not particularly effective. In this research, several tests ran on two types of data group - control and PD affected people. The dataset is collected from the Parkinson's Progression Markers Initiative (PPMI) repository. Then MRI slices are processed from selected data group into the CNN models. Three CNN models are sent into this thesis work to extract features from the data group. The CNN models are InceptionV3, VGG16 and VGG19. These models are used in this research to compare and get better accuracy. Among these models VGG19 worked best in the dataset because the accuracy for VGG19 is 91.5% where VGG16 gives 88.5% and inceptionV3 gives 89.5% on detecting PD.

Keywords: Parkinson's Disease (PD), neurological condition, dopaminergic neurons, PPMI, MRI, CNN, extract features, VGG3, VGG16, VGG19, accuracy.

Dedication

It is our genuine gratefulness and warmest regard that we dedicate this work to all our loved ones for their love and inspiration.

Acknowledgement

Firstly, all praise to the Great Allah for whom our thesis have been completed without any major interruption.
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And finally to our parents without their throughout support it may not be possible. With their kind support and prayer we are now on the verge of our graduation.

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

∇ Triangle Down

η Eta

ψ Psi

ξ Xi

AI Artificial Intelligence

ANN Artificial Neural Network

$BOLD$ Blood Oxygen Level Dependent

CNN Convolutional Neural Network

DL Deep learning

DST The Discrete Sine Transform

$fMRI$ Functional Magnetic Imaging

KNN k-nearest neighbors

LDA Latent Dirichlet Allocation

$MDS - UPDRS$ Development Clutter Society-Unified Parkinson's disease Rating Scale

ML Machine Learning

MRI Magnetic Resonance Imaging

NN Neural Network

PD Parkinson's Disease

PET Positron Emission Tomography

QDA Quadratic discriminant analysis

$ReLU$ Rectifed linear unit

REM Rapid Eye Movement

ROI Region of Interest

SGD Stochastic Gradient Descent

$SPECT$ Single Photon Emission Computed Tomography

SVM Support Vector Machine

$SWEDD$ Scans Without Evidence of Dopaminergic Deficit

UCI University of California Irvine

$UPDRS$ Unified Parkinson's Disease Rating Scale

Chapter 1

Introduction

Parkinson's Disease is a dynamic neurodegenerative dis- arrange characterized by several motor and non-motor attributes coming about in a stamped lessening within the pathos of living [5]. It could be a moving neurological clutter where signs move to compound ceaselessly. This disease may be an outline of extrapyramidal clutter that have not any self-evident philosophy. Apart from that there are other sorts of extrapyramidal clutters implied to as Parkinsonism with variant philosophies like vascular, defilement, damage, soporific-generate, Carbon monoxide toxin, etc. Besides other sorts of neurodegenerative extrapyramidal disarranges categorized as Parkinsonian conditions like energetic super atomic loss of motion and various-process rot. The first assurance of this disease is ordinarily difficult. Pressure and discouragement are pre-existing character disarranges in the patients who have PD. Right presently, there's no recuperate for PD, but drugs and surgeries are few remedy choices to diminish Parkinson's malady side impacts.

This disease is an ordinary movement clutter. Moreover, After Alzheimer's disease it is the 2nd most common neurodegenerative vacuolization. It is classified by the slow misfortune of muscle movement and the degree of disability changes in individuals. Those who have adult-onset PD are generally 60 but early-onset PD and juvenile-onset PD also exists. Agreeing to PD establishment, the predominance of PD increments with oldness but 4% of the patients with PD are analyzed sometime recently age 50 [69]. About 60,000 patients within the U.S. are analyzed with PD every year [69]. It does not incorporate thousands of occurrences that are undiscovered. Around the world, and evaluated 7 to 10 million individuals are suffering from this disease. Among the Caucasians it is more common. Men suffer from Pd more than women and it is 1.5 times. Inordinate disclosure to poisons like herbicides and pesticides could be a possible chance figure for PD. Those people who have a family history of this disease are little populace moreover at the liableness of creating PD.

It is the impact of the exhaustion of dopaminergic neurons within the substantia nigra and basal ganglia [47], [53]. It is classified by four main side effects: shake, sprawling insecurity, muscle inflexibility, and gradualness of motion. Sub-classified of PD are not simply determined but are classified constructed on their seriousness amounts. Mild, moderate, and advanced PD are known as the classes of this disease evaluation. Around 80% of patients with PD are regarded as idiopathic since of their obscure origin of philosophy while enduring twenty percent of patients are assumed

to be inherited [19]. Varieties within the hereditary are mixed of indisputable qualities that lift the hazard of PD. Thinks about have detailed that change within the LRRK2 (leucine-rich rehash kinase 2), PARK7 (Parkinsonism Related Deglycase), PRKN (Parkin RBR E3 Ubiquitin Protein Ligase), PINK1 (PTEN-induced putative kinase 1) or SNCA (alpha-synuclein) convey to the chance of this disease [16], [18], [24], [27], [34].

There are numerous plates to assess impedance and inability (step and seriousness) in this disease. Amid all of them, the Unified Parkinson's Disease Rating Scale (UPDRS) and the Hoehn and Yahr (HY) scale are the foremost normally utilized [59]. UPDRS gives an all-around review of inability and impedance by assessing the most liable medical highlights of this disease, though the HY scale provides a net evaluation of malady movement through a scaffolding which orbits from (no symbol of malady) to 5 (extreme). The Development Clutter Society-Unified Parkinson's disease Rating Scale (MDS-UPDRS) is the overhauled and changed adaptation of the unique UPDRS with modern things given to a few non-motor parts of PD to make it wider than the professional scale [11]. Former vital contrasts incorporate consumed scotching directions and definitions, and accentuation on disabilities and inabilities related to milder side effects and symbols.

A massive range of genetic variations have been identified as threat factors to boost PD. Recently, proof has emerged that the same genetic chance variants also decide positive medical points of the disease [30]. Genetic factors probably play an important function in identifying PD subtypes; however, little work has been achieved to include genetic information into data-driven algorithms to pick out subtypes. One related current study described the inclusion of genetic facts to guess the yearly pace of fluctuation in combined grades from the Movement Disorder Society-Unified Parkinson's Disease Rating Scale [23].

The chronicle of this malady grows from 1817, when British pharmacist James Parkinson distributed a paper on the trembling Paralysis, to present-day clips [4].In the beginning, Parkinson's explanations, other people had already delineated options of the sickness that would conduct his name, whereas the twentieth century outstandingly meliorate data of the sickness and its interventions. In English, PD was at that point familiar as loss of motion paralysis which is known as shaking paralysis. The term "Parkinson's disease" was invented in 1865 by William Sanders and afterward popularized by French neurologist Jean-Martin Charcot. Parkinson's illness could be an energetic anxious framework clutter that impacts development [10].

A few early sources portray side effects taking after those of PD. An Egyptian papyrus from the 12th century B.C. notices a lord dribbling with age and the Book of scriptures carries several bibliographies to microseism. An Ayurvedic restorative treatise from the 10th century B.C. portrays an illness that advances with tremor, need of development, dribbling and other side effects of PD. Also, this illness was hardened with cures determined from the mucuna household, which is wealthy in L-DOPA. Galen composed almost an infection that nearly certainly was PD, depicting tremors that happen as it were at relax, postural shifts and loss of motion.

Later on, Galen there are no familiar bibliographies uniquely attached to this disease till the seventeenth century [7]. John Seeker given a careful depiction of the illness, which may have granted Parkinson the thought of assembling and portraying patients with "loss of motion Paralysis". At last, Auguste François Chomel in his pathology dissertation, which was modern to this paper, involved a few portrayals of anomalous developments and inflexibility coordinating those seen in this disease.

In Parkinson's disease, side impacts start gradually, presently and after that starting with a scarcely recognizable frisson in fair one hand. Frissons are familiar, hardly the clutter as well usually reasons strength or abating of advancement. Inside the first stages of Parkinson's contamination, go up against may show up little or no aspect.

The term FMRI more often than not alludes to the imaging of brain actuation utilizing different MR procedures. By the late 1980's it was known that regional cerebral blood stream expanded close zones of neuronal movement, and low-resolution PET studies had already documented this phenomenon in humans [13].

As a brain imaging method FMRI has a few critical focal points: The round and hollow subway of an MRI scanner homes a capable electro-magnet. A normal inquire about the scanner incorporates an area quality of three teslas (T), almost fifty thousand times more noteworthy than the Earth's area [70]. The magnetic area inside of the scanner influences the magnetic cores of iotas. Ordinarily nuclear cores are arbitrarily situated but beneath the impact of an attractive area of the cores ended up adjusted with the heading of the area. The more grounded the area the more noteworthy the degree of arrangement. When demonstrating inside the same course, the small magnetic signs from person cores include up coherently coming about in a flag that's expansive sufficient to a degree. In fMRI it is the attractive flag from hydrogen cores in aqua (H2O) that's identified. Given the high affectability of the approach, it may behave utilize in a covering aspect. Relaxing-state useful MRI seems to demonstrate to be a profitable, non-invasive neuroimaging biomarker for neurodegenerative maladies like PD. The stream model-based, data-driven attempt on the full-brain betwixt-network network to segregate this disease patients from solid manages appears hopeful comes about with great precision and a high affectability. In this paper, utilizing fMRI information we are going attempt to distinguish the early stages of Parkinson's disease also using a machine learning approach into that. With the progression of Science and technology everything has gone machine subordinate. We are going to use diverse machine learning approaches like Random Forest Regression, Naive Bayes and also genetic algorithm to develop our study.

Characteristics of Parkinson's disease are dynamic misfortune of muscle ascendancy, which leads to shaking of the processes and brain whereas at rest, solidity, gradualness and disabled adjust. As the reason declines, it may stimulate to be troublesome to pass, conversation, and total basic assignments. The evolution of this disease and the degree of impedance shift from person to person. Some of the people with Parkinson's disease alive retentive beneficial lives, though others ended up debilitated much more rapidly. Complications of Parkinson's such as dropping related

to traumas or pneumonia. Be that as it may, considers of obvious populaces with and without Parkinson's disease recommend the life hope for individuals with the disease is almost the same as the common populace.

1.1 Problem Description

There are numerous investigate works going on Parkinson Disease (PD) which appeared to be the second most common malady within the world and it still more expanding presently each day. This circumstance leads to construct a choice bolster framework for PD. Presently every day's computational devices have been outlined for helping the specialists to form choices around their patients. Artificial Insights procedures are one of the essentials of physical visits to the clinic for observing and medicines are troublesome. Broadening get to the Web and progressed media transmission frameworks transfer speed offers the plausibility of inaccessible observing of patients, with considerable openings for bringing down the bother and fetched of physical visits. Be that as it may, in arrange to misuse these openings, there's the need for dependable clinical observing instruments.

Even though the condition is fundamentally characterized by tremors and trouble in strolling, most patients to endure from discourse issues, especially slurring and what's known within the field as frail voice. Whereas 89% of individuals with PD involvement a few sorts of discourse issues. So, if the classification rate of Parkinson infection is tall at that point it's conceivable to anticipate Parkinson in early organize. Typically, the conclusion is supported on the restorative outline and neurological testing conducted by meeting and watching the understanding in individuals utilizing the Bound together Parkinson's Disease Rating Scale (UPDRS). It is exceptionally troublesome to anticipate PD based on UDPRS in early stages, as it were 75% of clinical analysis of PD are affirmed to be idiopathic PD at dissection. In this way, programmed strategies based on Artificial Intelligence are required to extend the diagnosis is exactness and to assist specialists to create way better choices.

1.2 Objective and Motivation

Parkinson's disease (PD) could be a long-lasting chronic clutter of the Main Apprehensive Framework which causes a differing set of indications extending from tremor to cognitive disability, mental trip, dementia, rest disorders, etc. About 10 million people within the world endure with Parkinson's malady [70]. Every year, in Bangladesh roughly 1600 individuals pass on from Parkinson Disease. Till presently there's no remedy for PD [70]. In any case approximately ten a long time sometime recently the onset of tremor or engine indications, the dopaminergic neurons start to alter. A few premotor indications of Parkinson's malady (at an early organize) incorporates diminish the sense of scent, clutter in Rapid Eye Movement (REM) rest, small handwriting, trouble in moving, etc. An early conclusion of PD comes about in viable administration and evasion of superfluous therapeutic tests, treatments, costs, security dangers, etc. Parkinson's at an early organize is normally identified utilizing brain checks like MRI, fMRI, SPECT, PET, etc.

Till nowadays, in many hospitals, these pictures are deciphered by doctors; with included plausibility of person mistake. Considering, it was detailed that the pooled exactness of medical determination of this disease is as it were 80.6% [36] which actuated us to reach up with an unused and straightforward advance to distinguish Parkinson's malady at a first organize consequently utilizing Picture Handling and Artificial Neural Network. Adjusting this innovation in healing centers or demonstrative centers can increment exactness in the determination of Parkinson's and spare cash and time.

The research objectives of our thesis project are given below:

- The first reason of this thesis work has been done to search a better way for detecting Parkinson's Disease. This thesis paper aims to detect Parkinson's Disease using data from fMRI(Function Magnetic Resonance Imaging) to differentiate PD effected people.
- This thesis project initiate application of Convolutional Neural Network(CNN) for detecting Parkinson's disease easily. This research project develop three models for detecting Parkinson's Disease by integrating Deep Neural Network and Transfer Learning.
- In this thesis , we evaluate the accuracy and result of this model.We used VGG19,VGG16 and InceptionV3 for better accuracy and comparison. We provide advice on developing the model.

We would like to research more of this topic and we will try our best to find an easier, cheaper and better process to detect PD.

1.3 Thesis Overview and Orientation

As Parkinson's Disease is an exceptionally difficult malady to analyze clinically, so for our thesis paper, in chapter two We will discuss about the previous research work of this disease detection. Then in chapter three, We discuss how we use machine learning in our thesis work, next we go through all sorts of indications of Parkinson's disease. We will classify all sorts of major indications that cause Parkinson's Malady. We will use neuroimaging techniques and CNN models to detect Parkinson's Disease. After that, chapter four presents the proposed model of the research. For expansion, we will explain workflow, data description and analysis, data processing, in the CNN part we discuss about the CNNs, activation function, cost function and feature extraction. Chapter five demonstrates the results found in our research which includes implementation, result and discussion where we make comparison between accuracy of using different architectures. Finally, Chapter six, concludes the thesis which includes future work also.

Chapter 2

Literature Review

In the recent years, neuroimaging techniques have proven effective in the healthcare domain for classification or segmentation of medical images in detection of Parkinson's Diseases. In paper [31] authors used k-NN for detecting of PD as the base classifier. Their dataset contained train and test data and there were 1040 record files of 40 subjects of healthy and PD affected patients. In their work, they diagnosed two classes and they were healthy (0) and PD affected (1). They implemented all the algorithms in matlab they were - kNN, LDA and QDA. In order to increase classification accuracy they investigated the best parameters by using an ensemble method which was random subspace. They got 27.65% rate as the lowest classification error.

In paper [35] authors invented feature selection for speech pattern classification of PD. Their data was in voice format. Authors used dataset of two groups. First group was PD affected and there were 20 subjects where 6 female and 14 male. Second group was healthy and there were 10 female and 10 male. In their paper, LDA was used for evaluation of the performance of feature selection. There were many features such as - Jitter, Shimmer, AC NTH, HTN, Median pitch, Mean pitch, Standard deviation, Minimum pitch, Maximum pitch, etc. From their result, authors stated that, insignificant features can be removed by using fuzzy entropy[35].

In paper [42] author used a machine learning model which was predictive and effective enough to diagnose PD. They conducted their research using a PD dataset which was the voice recordings of PD patient and unaffected people. Their voice dataset was collected from UCI repository. They created the model from voice recordings where they pre-processed voice recordings so that it can easily be analyzed by ML algorithms. They used Pearson Correlation method for classification and this method mainly used on numerical data.They used top 10 features for the model and excluded all. They implemented a validation named K-fold cross validation to train all the data of the model. They have tested many models such as - SVM, neural networks, decision forests, etc. and they also cross validated. But Boosted Decision Tree provided the best accuracy. The accuracy produced by the model was 91.2105% which was average of all k folds and best accuracy was 95.0%.

Fayyazifar and Samadiani used the genetic algorithm in order to detect PD at early stage [43]. They proposed a method from voice recordings where they achieved respectively 96.55% and 98.28% success rate of PD detection by using AdaBoost and

Bagging on the process of classification. They used machine learning techniques in order to detect early PD. In order to reduce the size of feature vector and select the optimal feature authors employed a Genetic algorithm. In their paper, they classified input data by using AdaBoost and Bagging into two categories they are healthy and patient. Their first proposed method was using AdaBoost and Genetic algorithm where number of features were 6 and the accuracy was 96.55%. On their second proposed method was Bagging and Genetic algorithm where number of features were 7 and the accuracy was 98.28%.

In paper [46] they used data mining and ML approach in order to detect the PD. Their system provides an interface which is simple and efficient enough to upload the data of PD and then create a model and generate report from that related model. The system was able to predict whether a person has PD or not. Their system was a web application which was open to all and everyone was able to upload or download, classify and analyze the PD data. Since it was open for everyone, it was known as OPSDS. This system was able to connect researchers, patients, doctors, etc. who were connected with PD across the world which made the system more efficient and accurate. In order to, analyze and predict user can up-load dataset where he need specify dataset description. User can create models from the available datasets. After that, user can generate reports based on the model's name, modified date, classification, errors, etc. The main goal of the system was the prediction of PD by comparing the patient data with the existing data on the system. They used two datasets and both were speech data. They developed two models based on those datasets and K-NN algorithm was used to classify. Their dataset 1 had 90% accuracy and dataset 2 had 65% accuracy.

In paper [55] authors proposed a methodology to detect PD by using image processing of CT images of brain. Their proposed methodology can predict whether a person is affected with PD or not and it can take real time input. Authors have used dataset form UCI where total image sample were 32. First, the CT scanned brain image data was used. CT scan describes the PD affected person's image. After that, gray scale converter was used for converting color images of CT scanned to black and white images. Then preprocessing was used to remove any unwanted distortions in the images and increase the features of the images. After that, anisotropic filter was used by the authors to improve the quality and texture of the images and remove aliasing effects from images. To represent PD or non-PD image was segmented which were taken from CT scan. Bounding box was used on a specific region of a brain at the CT scanned images to identify PD affected brain. After that, white segment of an image in the PD affected part was highlighted which was detected as PD. Authors used 32 samples where 21 files were true positive, 6 files were true negative, 3 files were false positive and 2 files were false negative.

H. N. Pham et al. [64] did research on detecting PD by using voice and image test. They used various ML models on both voice and spiral data and they got accuracy which was at excellent level. From vocal dataset they used k-means clustering and Pairwise correlation. They got 95.89% of accuracy by using 3 models in combination. Their best accuracy was 99.6% which they got from DST and k-Nearest classifier. They got 98.8% and 94.9% accuracy by using Logistic regression and AdaBoost on

the STCP and SST. The result of their spiral test was gained by the combination of DST, SST and STCP. Moreover, they had a multi-modal approach on a smartphone app to carry PD test more easily.

In paper [65] authors proposed a hybrid machine learning method for detection of PD. It has two stages and they are data pre-processing and classification. Authors used dataset of UCI machine learning and there were 756 samples and 753 features. Amongst those 756 samples there were 192 samples which were belong to healthy and the rest 564 samples were belong to patients. Authors used speech signal methods to obtain features from the dataset. Those data were taken from 188 different patients and there were 107 men and 81 women whose ages was between 33 to 87 years. At first, authors applied SMOTE method to fix the imbalanced distribution of class. Then they converted that dataset into a balanced class distribution using SMOTE method. After that, random forest is applied by the authors to create a forest to combine the results made by the decision trees and training was done by bagging method. The new PD dataset was classified by their RF classifier. Authors evaluated their proposed method by using the accuracy of classification, Precision, Kappa value, F-measure, etc.

In paper [15] authors applied two training algorithms - LM and SCG of neural network in order to diagnose PD. LM helps to find minimum error on the surface and skips plateaus by taking larger steps. LM does this by using VGD and GN rules. To fix large scale problems author used SCG on their research. Authors used dataset of voice data and there was total 195 samples. 147 samples were PD affected. Authors differentiated healthy peoples from PD affected peoples. Authors obtained their experimental results by using LM and SCG. Their highest training accuracy was 97.86% which was achieved at from 25 units by using LM algorithm. Furthermore, authors attained 79.06% training accuracy from 10 units by using SCG. Author stated that, LM algorithm gave higher accuracy rate than SCG even in testing phase. Authors got 72% to 93% testing accuracy by using LM. On the other hand, they got 67% to 79% testing accuracy by using SCG.

Authors named Adeli, Wu and Saghafi acquired the data from multi-modal neuroimaging data to diagnose Parkinson's Diseases by investigating the brain areas which are known to be affected at the early stages. They proposed a joint kernel-based feature selection and classification framework which induced the excellent overall performance for analysis for Parkinson's disease [38]. Another group constructed a cascaded multi-column RVFL+ (cmcRVFL+) framework for the single-modal neuroimaging-based Parkinson's Disease diagnosis without the additional neuroimaging modality as privileged information. Their results on both the transcranial sonography dataset and the magnetic resonance imaging data set for Parkinson's Diseases showed that the cmcRVFL+ has the potential to be flexibly applied to various single-modal imaging-based CAD [62]. A recent paper showed the diagnosis of thirty patients with idiopathic olfactory loss who participated and claimed non-invasive transcranial sonography very useful in figuring outpatients probably at danger to expand Parkinson's Diseases [9].

In numerous cases, no reason can be officially prominent and olfactory disorder is at

that point taken into consideration to be idiopathic. Olfactory disorders because of sinonasal disease are not unusual and widely recognized to clinicians. Medical and surgical treatment by and large permits determination of olfactory complaints. Since this is applied by the noninvasive process so it does not require inserting an instrument through the skin or into a body opening of patients. Another study developed an advanced MRI method for detecting Parkinson's Disease which relies upon an image constructed as a ratio of pictures from two inversion recovery sequences (one generating a white matter suppressed image, the other a gray matter suppressed image). From the segmented image a measure of disorder severity, they calculated the Radiological Index (RI) for every subject and the work is consistent with the proposition that MRI, when properly configured, is a highly sensitive marker for Parkinson's Disease [12]. Another research study presents in-vivo evidence that brain stem damage may be the primary identifiable level of Parkinson's Disease neuropathology, and that the identity of this steady damage together with other factors could assist within advance diagnosis in the future. This damage can also explain some non-motor signs and symptoms in Parkinson's Disease that frequently move earlier than diagnosis, such as autonomic dysfunction and sleep disorders [14].

To map biochemical changes inside the brains of people with mild-moderate Parkinson's Diseases a research group quantified neurochemical profiles of the pons, putamen and substantia nigra using 7 tesla (T) proton magnetic resonance spectroscopy. This study gives in vivo proof for an alteration within the GABAergic tone inside the lower brainstem and striatum in early-moderate Parkinson's Diseases, which may also underlie disease pathogenesis and can offer a biomarker for disease staging. But they could not determine the primary or secondary alterations and the impact of treatment on them [22]. Two Indian people proposed a unique and advanced staging for Parkinson's Diseases using the MDS-UPDRS functions and the HY scale, and developing prediction models to estimate the level and severity of PD using machine learning techniques such as ordinal logistic regression (OLR), support vector machine (SVM), AdaBoost- and RUS Boost-based classifiers. Such equipment can be a useful resource in detection and diagnosis, and thereby, assisting in taking effective healing decisions in Parkinson's Diseases [60].Furthermore, another paper reviewed Parkinson's Disease etiologies, development, and specifically measurable indicators of Parkinson's Disease which includes neuroimaging and electrophysiology modalities [54].

Creating a demonstrate for first PD discovery Prashanth R. et al. [29] utilized SBR or striatal binding portion values from I-Ioflupane SPECT filters. For making these specific demonstrate back vector machine (SVM) and RM has been utilized. For SBR values the four striatal locales to be specifically cleared out and right caudate and cleared out and right putamen is utilized. When we compare the two models utilized, it was watched that SVM when utilized with RBF bit and prognostic show based on multivariate relapse demonstrate both allow tall exactness for recognizing early PD conjointly separating early PD from SWEDD. In another work of the same creators, the individual creators created a classification show to isolated early PD patients from typical or SWEDD patients by SPECT checking information of ordinary patients, PD patients and SWEDD patients to see which locale of the filter appears most tall movement. To create a demonstrate for early PD discov-

ery Prashanth R. et al. [29] utilized SBR or striatal official proportion values from I-Ioflupane SPECT filters. For building these specific demonstrate back vector machine (SVM) and re-lapse demonstrate (RM) has been utilized. For SBR values the four striatal locales to be specifically cleared out and right caudate and cleared out and right putamen is utilized. Comparing the two models utilized, it was watched that SVM when utilized with RBF bit and prognostic show based on multivariate relapse demonstrate both allow tall exactness for recognizing early PD conjointly separating early PD from SWEDD. In another work of the same creators, the individual creators created a classification show to isolated early PD patients from typical or SWEDD patients by SPECT checking information of ordinary patients, PD patients and SWEDD patients to see which locale of the filter appears most tall movement. The classification demonstrate is made based on highlight extraction after normalizing and fragmenting information. The highlight extraction has been performed in two forms. One is analyzing the shape of these districts which gave them16 highlights and another is fitting a cubic surface to watch escalated on those specific districts which gave them 14 highlights. Besides this, the particular highlights are too compared with SBR based include utilizing Random Forests technique [29].

Choi H. et al. built up a demonstrate which can correct the human mistake where a quiet is analyzed clinically as PD but after performing a visual examination of FP-CIT SPECT appear no prove of dopaminergic insufficiency. Although dopamine transporter imaging (DAT) effectively distinguish dopamine insufficiency but still now and then it is conflicting due to high sensitivity (67%) and low specificity (67%) in patients at early organize of PD. Consequently, the objective of their work is utilizing profound learning-based demonstration in making a mechanized FP-CITSPECT translation framework that can separate PD patients with no specific symbols of PD. For elucidation of these pictures CNN or deep convolutional neural network was utilized which learn picture highlights from each set of preparing information to create two nodes-one for PD and one for typical control. Addition-ally these models will partitioned SWEDD patients from patients wrongly clinically analyzed as PD [40].

Paul D Acton and Andrew Newberg utilized artificial neural networks to mimic human design acknowledgment aptitude that can analyze and appear comparative comes about as conventional ROI examination. The ANN was, to begin with, prepared with a known dataset where 46-pixel values of striatum were passed into the input hub which in turn was passed into the covered-up layer. The covered-up hubs gave the last result as two conclusion hubs, one of which shown understanding and one as typical. After these obscure datasets were connected on the ANN which come about into a precision of 94.4% which is the most elevated of other strategies which are Mean ROI, Best ROI, mean spectator and Best Observer included within the specific test [61].

Chapter 3

Background Study

3.1 Parkinson's type

Parkinsonism may be a term utilized to depict the collection of signs and indications found in Parkinson's disease (PD). These incorporate gradualness (bradykinesia), firmness (rigidity), tremor and lopsidedness (postural flimsiness). Conditions other than PD may have one or more of these indications, mirroring Parkinson's. There are some diseases which are easily confused with Parkinson's like Hepatolenticular degenention, Multisystem atrophy, Cortical basal ganglia denaturation, Essential tremor, Huntington's disease, Progressive supranuclear paralysis, Diffuse levy body disease etc [49]. These are shown in figure 3.1. Maximum people with parkinsonism have idiopathic Parkinson's disease, additionally known as Parkinson's. Idiopathic implies the reason is obscure. The foremost not unusual side effects of idiopathic Parkinson's are tremor, inflexibility and gradualness of movement. This sort has a tendency to reply properly to medicine that works by expanding or substituting dopamine atoms inside the brain [66]. Corticobasal Degeneration (CBD) is a rare type of parkinsonism that influences individuals from the age of 40, ordinarily between the ages of 50 to 70. It tends to influence one aspect of the body more than the other initially, progressively spreading throughout a couple of a long time. CBD has likenesses with Progressive Supranuclear Palsy (PSP). A few individuals with CBD go on to develop PSP, and vice versa. Some of the symptoms of CBD are trouble controlling the appendages on one side of the body – regularly known as 'alien limb' disorder – as arms or legs could appear to move independently, numbness and misfortune of facilitated development in one hand (apraxia), making regular work such as dressing, writing and eating troublesome, muscle solidness (rigidity), shaking (tremor), jerky or ungainly development and fits (dystonia), adjust and coordination issues, etc [51].

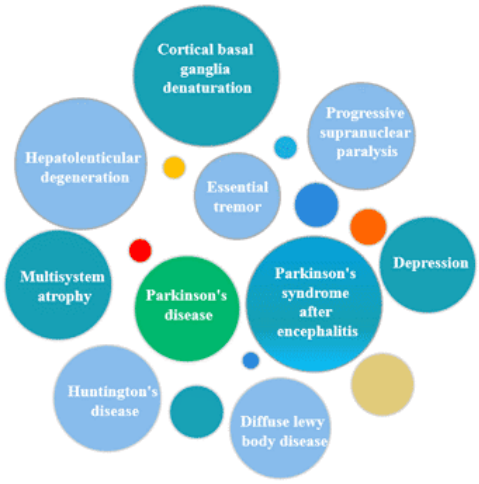

Figure 3.1: Diseases easily confused with Parkinson's

A little number of individuals create parkinsonism after taking certain medicines. Individuals with Parkinson's may moreover discover their indications get more regrettable after they utilize these medications. This is known as drug-induced parkinsonism. The drugs included are by and large those that block the activity of dopamine, the neurotransmitter that's slowly misplaced within the brains of individuals with Parkinson's. The side effects of drug-induced parkinsonism have a tendency to remain the same. As it were in uncommon cases do, they advance as the side effects of Parkinson's do. Most individuals will recover inside months, and frequently inside hours or days, of halting the medicate that caused the dopamine block [52]. Vascular parkinsonism is additionally called cerebrovascular disease, this sort of parkinsonism is caused by an arrangement of small strokes, coming about within the passing of parts of the brain, driving to the Parkinson's disease-like symptoms. The condition frequently shows indications within the lower half of the body (walking challenges and urinary incontinence) and memory misfortune. It tends to be less responsive to commonplace Parkinson's illness medicine particularly because it advances. Vascular parkinsonism gets to be more common with age, particularly in individuals with diabetes [44].

Normal-pressure hydrocephalus primarily influences the lower half of the body. The indications of NSA are exceptionally comparable to those seen in vascular parkinsonism. The common side effects are strolling challenges, urinary incontinence and memory issues. Expelling a few cerebrospinal liquids through a needle within the lower back can help with these side effects within the brief term. On the off chance that there's advancement after this method, an operation to divert the spinal liquid for all time (known as ventricular drainage) can offer assistance within the long term [66]. Multiple System Atrophy (MSA) is another type of Parkinson's which is a dynamic neurological sickness (an illness of the nervous system). It is caused by an overproduction of a protein within the brain called alpha-synuclein which causes degeneration (decay) of nerve cells in a few zones of the brain (multiple systems). The three primary zones influenced are the basal ganglia, the cerebellum, and the brain stem. This cell loss can result in several issues, especially related to development, adjust and other autonomic (unconscious) body capacities (such as bladder function). These indications are exceptionally comparative to Parkinson's, but MSA advances

quicker and does not react as well to medication. Symptoms shift agreeing to which portion of the brain is influenced by the misfortune of nerve cells. Not everybody will encounter all side effects. Weakening is an exceptional person. A few of the foremost common indications are moderated developments, inflexibility or solidness, trouble turning in bed, trouble in starting development trouble in composing, composing may end up little and spidery, loss of adjusting and destitute coordination or clumsiness (ataxia), discourse challenges, trouble with fine engine aptitudes such as doing up buttons, issues with erection or male feebleness, misfortune of bladder control, counting urgency, visit urination or fragmented purging, frequently getting up a few times at night to pass pee, bowel issues, counting clogging, failure to sweat, cold hands, and feet, drop in blood weight when standing (postural hypotension), driving to discombobulation, blacking out or obscured vision, coat holder pain' (torment in neck or shoulders) as a result of low blood pressure, issues with swallowing, feelings that are effortlessly stirred or tend to alter rapidly, discouragement, uneasiness or a feeling of being overpowered delicate voice especially when tired, eager rest, loud breathing, counting snoring when sleeping, etc [67]. The patient of parkinson's disease has several typical appearance such as stooped posture, rigidity, flexed elbows wrists, masked facial expression, forward tilt of trunk, reduced arm swining, slightly flexed hips knees, trembling of extremities, shuffling, short-stepped gait etc which are shown in figure 3.2 [56].

Figure 3.2: Typical appearance of Parkinson's Disease.

Progressive Supranuclear Palsy (PSP) is another most common degenerative sort of atypical parkinsonism. The normal age of the influenced individuals is within the mid-'60s. Side effects of PSP tend to advance more quickly than PD. Individuals with PSP may fall habitually early within the course of infection. Afterward side effects incorporate confinements in eye developments, especially looking up and down, which to contributes to falls. Those with PSP moreover frequently have issues with gulping (dysphagia), trouble in creating speech (dysarthria), rest issues, memory and considering issues (dementia), absent-mindedness, identity alter (loss of interest in conventional pleasurable exercises or expanded fractiousness, trouble standing up to motivations; improper conduct), trouble synthesizing a few distinctive thoughts into a modern thought or arrange, slowing of thought, trouble finding words (aphasia), etc [49].

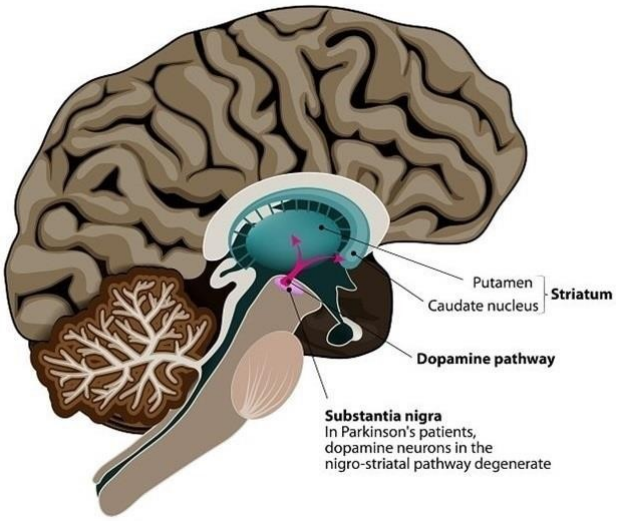

Figure 3.3: The causes of Parkinson's Disease.

Dementia with Lewy bodies (DLB) is a dynamic, neurodegenerative disorder in which anomalous stores of a protein called alpha-synuclein construct up in numerous zones of the brain. DLB is caused by the build-up of microscopic protein stores called Lewy bodies within the brain. These are connected to the passing of nerve cells, or neurons. It is vague why these Lewy bodies frame but, when they do, they interfere with the ordinary working of the brain. They are shown within the brains of individuals with DLB and Parkinson's. The hereditary qualities of DLB are still hazy, but it appears that there's a somewhat higher chance of creating DLB if closely related family individuals have the ailment, but this expanded hazard is still very low. A few of the foremost common side effects are fluctuating from readiness to confusion, destitute memory, destitute concentration, and consideration span, trouble finding the correct words when talking, visual visualizations, regularly including children and/or creatures trouble perceiving commonplace faces and objects, trouble in carrying out straightforward ordinary assignments, trouble with spatial mindfulness, trouble with strolling and adjust, frequently driving to falls, disturbed rest design and conceivably bad dreams, gradualness of development, solidness, tremor and facial concealing, gulping troubles, depression, blacking out, extreme sensitivity to neuroleptic (anti-psychotic) medicines, periodic changes in blood pressure, etc [28].

3.2 Basic Structure of the Human Brain

The Brain may be a forty-eight-dram that's launch inside the head close to the tactual organs [6]. An anthropomorphic head acts like a manage center for every capacity of a person's body [57]. The brain overdoes the physical body care of the interior and exterior including by making a regular stream of tactual signals. Probably, [45] it outlines the noteworthiness of cognizant and unconscious intellect. Memory, sentiments, inventive energies, experiences, breathing, interior temperature and emanations of organ are a few things carried out by the brain. There are five resources in a human body through which the brain gets information of the outside world. [58] These are hearing, locate, fragrance, taste, touch. The brain to boot competent of dealing with our understanding to a particular circumstance, talk, working of our members and various organs inside our body. It as well oversees our response to a repulsive circumstance by controlling our heartbeat. A brain is made of 3 main components; Brain Stem, Cerebrum, Cerebellum. The different brain regions that are affected by PD are shown in figure 3.4.

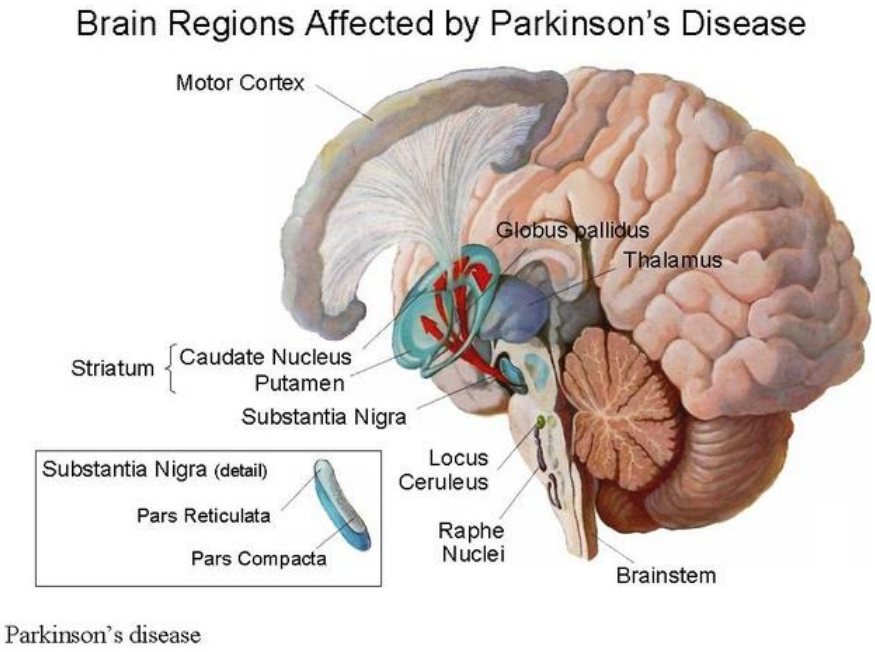

Figure 3.4: Brain Regions affected by Parkinson's Disease.

3.2.1 Brain Stem

It interfacing the spinal edge along with the brain, it is called the foremost second-rate zone of the head. The brain stem encourages as a hand-off center meddle the spinal line to the cerebrum and cerebellum. [58] Basically, Brain stem are of three regions; medulla oblongata, pons, midbrain. The brainstem is made out of a mix of dim and white matter is called reticular arrangement. Which regulates the body's tendon tone and behaves as a switch that manages the brain wake and rest cycles. Besides, the brain stem directs capacities related to homeostasis, blood weight, oxygen levels, heaving, wheezing, hacking and swelling reflexes. A brain is compiled of 3 main components; Brain Stem, Cerebrum, Cerebellum.

3.2.2 Cerebellum

It is the moment grade to cerebrum along with the back of Brain stem. It is rumpled and hemispheres in shape [21]. It acts the errand to control manipulate capacities such as altering, posture, arranging muscle works out. The Cerebellum attends the synchronization and guilefulness of motor exercises such as composing, talk and strolling.

3.2.3 Cerebrum

It is the largest section of the brain containing both the cleared out and right parts of this globe [71]. The fifty percent of this globe is associated with a course of action of strands called corpus callosum that transfer information from one side to the other side. Each fifty percent of the globe handles the converse side of the body. [58] For the event, within the occasion that one perseveres from a brain tumor on the correct fifty percent of this globe than they would encounter frail or paralyzes through the cleared outside of the body, awful habit versa. It works that way because there are many errands performed autonomously by each side of the equator. Such as; the right side of the equator controls creative energy, melodic capacities, spatial capacity, though the cleared outside directs talk, composing, calculations, comprehension.

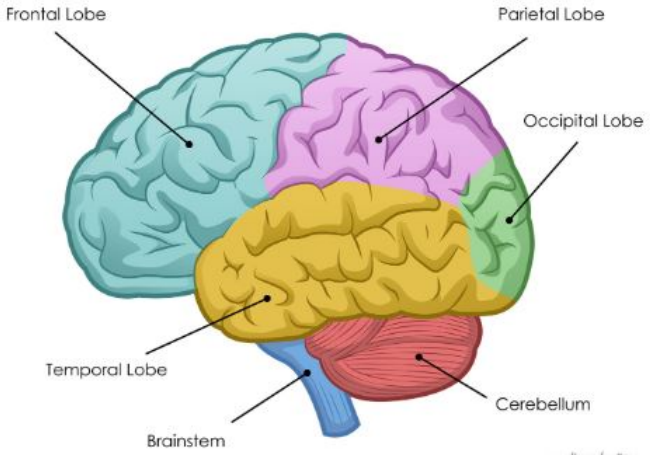

Figure 3.5: Different parts of the brain.

Each fifty percent of the globe may assist be classified into four unmistakable areas known as lobes. These are frontal, parietal, occipital and temporal lobe (Figure 3.5). Each lobe is dependable in performing particular a specific sort of work.

3.2.4 Frontal Lobe

The frontal lobe is a part of the human brain that deals with critical cognitive abilities in person, such as eager expression, judgment, issue handling, sexual behaviors, memory and tongue. It is, in pith, the "control panel" of our identity and our capacity to communicate.

It is additionally mindful for essential engine work, or our capacity to deliberately move our muscles, and the two key regions related to discourse, counting Broca's area. The frontal lobe is bigger and more created in people than in any other organism. As its title demonstrates, the frontal projection is at the front of the brain. The correct side of the equator of the frontal projection controls the cleared-out part of the body, and bad habit versa. The frontal projection is additionally the foremost common put for brain damage to happen. Frontal projection destroy can make shifting in identity, restricted facial aspects, and trouble in deciphering one's environment, like they are not being able to satisfactorily survey chance and harm. spoil to the frontal flap of the brain causes a run of side effects, counting engine shortcoming and behavioral issues. The frontal projection may be a moderately huge projection of the brain, expanding from the front of the brain nearly midway towards the back of the brain. An assortment of conditions can harm the frontal projection, counting stroke, head injury, and dementia. Symptoms of harm to the frontal projection can shift since there are so numerous capacities carried out by the frontal flaps. These side effects may incorporate one or more of the following: On one side of the body shortcoming or one side of the face, shortcoming causes Falling Failure to issue fathom or organize tasks Diminished creativity Disabled judgment Diminished sense of taste or smell Depression Changes in behavior Moo motivation Moo consideration span, effortlessly distracted Diminished or expanded sexual intrigued or unconventional sexual habits Incautious or unsafe behavior. Cure of frontal projection harm can incorporate several procedures, depending on the cause. For illustration, contamination can be treated with anti-microbial and brain tumors can be surgically expelled or treated with chemotherapy or radiation. Degenerative illnesses, such as Parkinson's infection, Huntington's malady, and dementia are as a rule treated symptomatically, but, at this time, there's small that can be done to anticipate conditions from worsening.The frontal Lobe mainly controls:

- Emotional traits
- Problem-solving
- Judgment

3.2.5 Parietal Lobe

The brain is isolated into several districts, but the range most people allude to when examining the brain is the cerebral cortex, or cerebrum. This developmentally modern locale of the human brain is displayed to all warm-blooded creatures, and for this reason it permits compound considerations instead of fair programmed and oblivious procedures. Neuroscientists isolate the cerebrum into four unmistakable projections: parietal, frontal, worldly, and occipital. Cause, the brain is additionally separated into right and cleared out halves of the globe, each flap has two partitioned districts.

In this way the parietal flap can be assist partitioned into the cleared out and right parietal lobes. The parietal flap rests close the beat and center of the cerebral cortex, fair behind the frontal flap and over the occipital and transient projections. The parietal-occipital sulcus isolates it from the frontal flap, whereas the sidelong sulcus—sometimes alluded to as the Sylvian fissure—separates it from the transient flap. The parietal lobe's two sides of the equator are isolated by the average longitudinal fissure. Parietal Flap evaluates estimate, shape, and introduction in space the parietal projection is crucial for tactile discernment and desegregation, counting the administration of savor, hearing, locate, skim, and scent. It is domestic to the brain's essential tangible zone, a locale where the brain deciphers input from other zones of the body. Inquire about recommends that, the more tactile input a locale of the body gives, the more surface zone of the parietal flap is devoted to that region.

For the case, the fingers and hands are an essential location for tactile information, so much of the parietal flap is committed to accepting and handling their input. Some of the other capacities of the parietal flap include: Recognizing between two focuses, indeed without visual input. Localizing touch: After you touch any portion of your body, your parietal projection empowers you to feel the sensation at the location of the touch and not, say, in your brain or all over your body. Coordination of tangible data from most areas of the human body. Visuospatial route and thinking: After you perused an outline, take after bearings, or anticipate yourself from stumbling over an unforeseen impediment, your parietal flap is involved. The parietal flap is additionally imperative for proprioception—the capacity to decide where your body is in space, counting in relationship to itself.

For occurrence, touching your finger to your nose without the help of a reflect could be a work of the parietal lobe. Some visual capacities, in conjunction with the occipital lobe. Assessing numerical connections, counting the number of objects you see. Assessing estimate, shape, and introduction in space of both unmistakable jolts and objects you keep in mind encountering. Mapping the visual world: many later thinks about propose that particular locales within the parietal projection serve as maps to the visual world. Coordinating hand, arm, and eye motions. Processing language. Coordinating attention. It mainly controls:

- Reading
- Sensation
- Body orientation

3.2.6 Occipital Lobe

The occipital projections are one of the four fundamental flaps or locales of the cerebral cortex. These projections are imperative for getting, handling, and deciphering tactile data. The occipital projections are situated at the back locale of the cerebral cortex and are the most centers for visual handling. In expansion to the occipital projections, back parcels of the parietal flaps and worldly flaps are moreover included in visual perception. Directionally, the occipital projections are situated back to the transient projections and second rate to the parietal flaps. They are found within

the biggest division of the brain known as the forebrain (prosencephalon). Located inside the occipital projections is the essential visual cortex. This locale of the brain gets visual input from the retina. These visual signals are deciphered within the occipital lobes. It mainly controls:

- Vision

3.2.7 Temporal Lobe

The brains of all well-evolved creatures, counting individuals, contain four flaps within the cortex, counting the occipital, parietal, transient, and frontal flaps. Found fair underneath the sidelong gap and crossing both crevices of the brain is the worldly flap. This imperative structure makes a difference handle tangible input, counting torment and sound-related boosts. It too makes a difference you get it dialect, hold visual recollections, and both prepare and keep in mind emotions. It mainly controls:

- Behavior
- Memory
- Understanding language

3.3 Image Processing

Image Processing implies orderly the application of different algorithmic programs to a picture data to upgrade the picture and extricate required data from the particular picture. It could be a sort of banner-making in which input signal is an image and provide maybe image or features correlated to that picture. This refining is among quickly improving favors. It shapes middle inquire about region interior building and computer science rules as well. There are 2 forms of plans used for image processing to be clear, analog and digital image processing. Image investigators utilize different basics of translation whereas exerting these visual procedures. Computerized image processing strategies offer assistance in the management of developed pictures by utilizing computers. The three common stages that all sorts of data require familiarization whereas utilizing computerized strategy are pre-refinement, upgrade, and show, data emotion. The primary steps related to any sort of picture handling are as takes after

1. Purport the input picture through procurement tools
2. Analyze and control the image
3. Get the yield picture or the result examination of the input picture.

3.3.1 Digital Image Processing

Digital image processing is the control of pictures via an advanced gadget. The three not unusual ranges that everyone variety of facts need to be enjoyed whereas making use of digital methods are pre-processing, enhancement, and display, records

extraction. There are three types of processing in digital image processing. They are the low-level image processing, mid-level image processing, and high-level image processing.

Low-level image processing Low -level image processing is that in which inputs and outputs are images which include image processing to decrease noise, comparison improvement and image sharpening.

Mid-level image processing Mid-level image processing is that in which its inputs are commonly pictures but its outputs are image attributes. It includes responsibilities including image segmentation, classification of image, image recognition.

High-level image processing High-level image processing is that in which its inputs are commonly attributed but its outputs are. It involves tasks making sense from a gathering of recognized items.

There are seven stages of Digital Image Processing:

1. Image acquisition
2. Image enhancement
3. Image restoration
4. Morphological processing
5. Segmentation
6. Object Recognition
7. Representation and description

3.3.2 Image Acquisition

It is the process of retrieving a completely unprocessed image for representing the visual characteristics of an object. It is the very first stage and generally it entails pre-processing.

3.3.3 Image Enhancement

Image enhancement is the technique of image filtering for a better-quality image. It deals with removing noise, improving brightness or sharpness.

3.3.4 Image Restoration

Image restoration is fixing the portion of the picture which contributes to the deformity of the picture. It is the process of improving an image with the help of mathematical models, such as removing blur from an image.

3.3.5 Morphological processing

It is the process of representing images in diverse ranges of decision. The method of changing over a grayscale image to a binary image in which each pixel has a strict value of either or 1 when distinguishing proof of objects inside a picture can be troublesome is called morphological picture processing. Different types of morphological processing are shown in fig 3.6 [63].

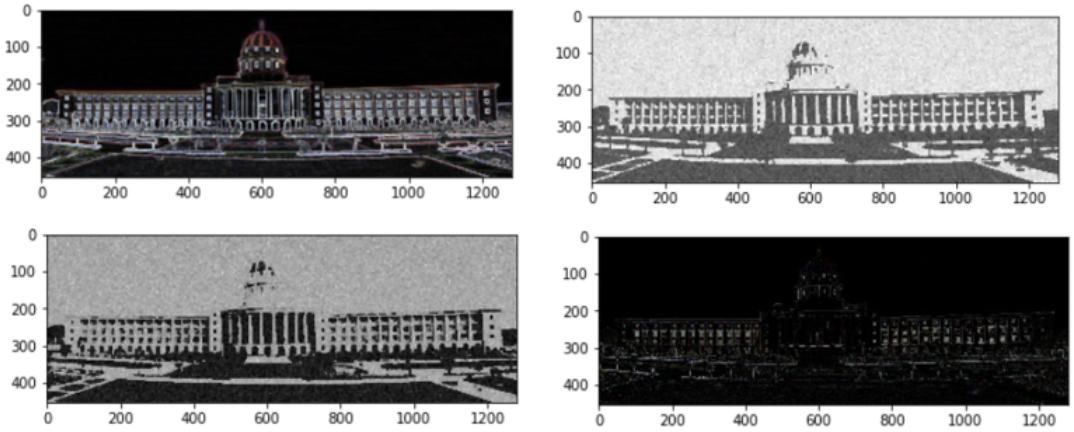

Figure 3.6: Morphological image processing

3.3.6 Image segmentation

It is the method of apportioning the image into multiple segments. Image segmentation is the method of dividing a computerized picture into multiple fragments or sets of pixels so that the picture is changed to something more important and less demanding to analyze. It is utilized for recognizing boundaries or objects in a given picture. In other words, what image segmentation does is dole out name to each pixel so that pixels with same names hold comparative characteristics Image segmentation is shown in fig 3.7 [63].

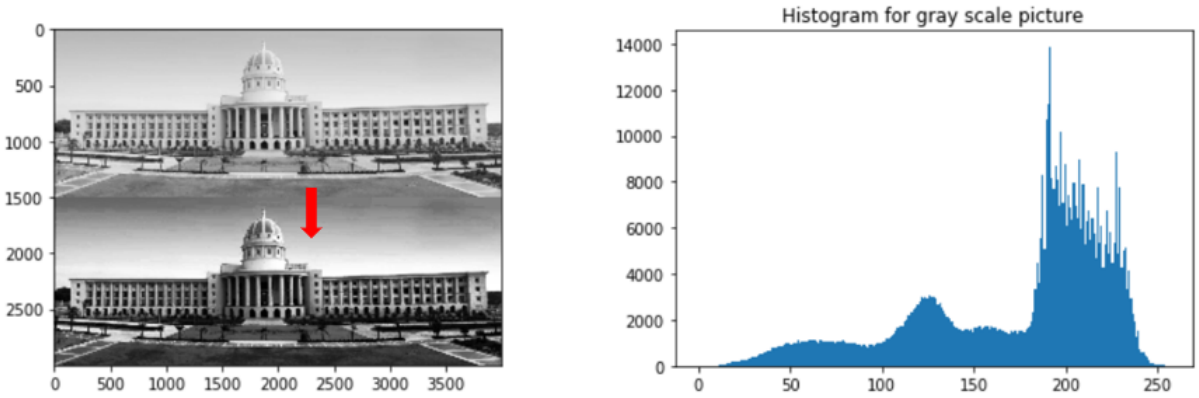

Figure 3.7: Image segmentation.

3.3.7 Object recognition

Object recognition is the method of assigning labels to an object. Object recognition strategies in digital image processing is the method of recognizing and recognizing an object from a given picture. There are different types of models such as feature extraction and machine learning models, deep learning models such as CNN, Bag-of-words models, gradient-based and derivative-based coordinating approaches can be utilized for object recognition.

3.3.8 Image representation and description

This can be the ultimate step in digital image processing. After an image is effectively portioned and all its objects and foundation have been separated, at that point it is vital to speak to the objects properly with their exact features. It includes representing an image in different forms:

- **Boundary Representation:** It facilities at the out of doors shape traits which include corners and inflections.
- **Regional Representation:** It centers on internal properties along with surface and skeletal shape.

3.4 Neuro-imaging techniques

Neuroimaging techniques play the first-rate function inside the evaluation of sufferers because it may identify alternate conditions of the brain. When neuronal action increments there's an expanded request for oxygen and the neighborhood reaction is an increment in the bloodstream to districts of expanded neural movement. FMRI presently encompasses a little but developing part in medical neuroimaging. it's far utilized in pre-surgical arranging to limit brain characteristics. Functional MRI utilizes the blood oxygen level subordinate (Bold) method to outline neural movement instead of axonal astuteness, identifying variations from the norm of the utilitarian organize instead of the auxiliary organize [50].

We can divide Neuroimaging techniques into two parts:

Structural imaging:
Structural imaging bargains with the structure of the brain to determine a large-scale infection.

Functional imaging:
Functional imaging permits the brain's data to be visualized because movement within the included range of the brain increments the digestion system.

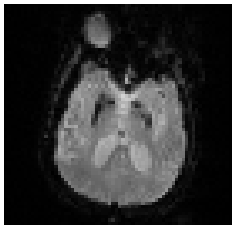

Figure 3.8: (a)

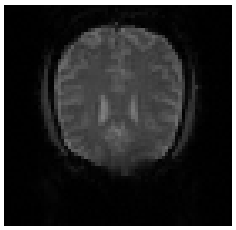

Figure 3.9: (a)

Figure 3.10: fMRI image of the brain.

From the above figure 3.10, These images are the end result of the excellent kind of fMRI strive. Whereas lying in the MRI scanner the challenge located a display which substituted among appearing a visual improve and being dull each 30 moment. Within the intervening time, the MRI scanner followed the flag for the duration of the brain.

3.5 Deep Learning

Deep Learning was evolved from ANN, and now it is a vital area of Machine Learning. Deep Learning models use hierarchical systems for connecting their layers. These models use simple linear or non-linear equations to attach the outputs among layers. They make use of low-level functions to transform into higher-level abstract features. They maintain track of the increasingly abstract representations of the input data and have the capability to frequently learn about those factors.

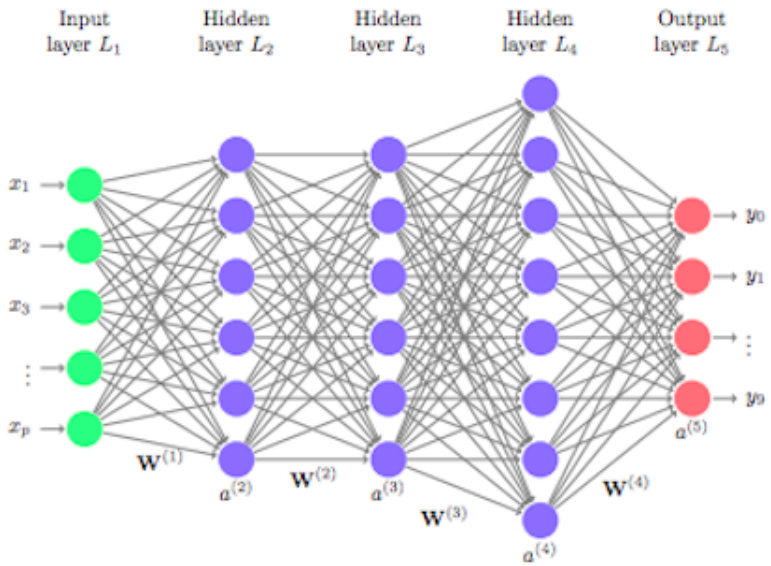

Figure 3.11: Deep Learning Model.

From Figure 3.11, DL works distinctly better than machine learning when it comes to solving complicated problems, like speech recognition, image classification, NLP. Deep Learning makes use of a huge quantity of parameters which makes the training time huge. Classical Deep Learning methods recommend using ANN, CNN, RNN and their altered versions. The softmax classifier is implemented upon the deep NN methods to derive the classification output [41].

3.6 Neural Networks

Neural Networks are multilayer networks that are used for classification, prediction and so forth. A NN has an input layer, which presents all of the input data and they are passed on to the activation function after assigning individual weights to each of the inputs. The activation function applies the required methods to produce the output that is later passed directly to the output layer [48].
There can be multiple hidden layers between the input and the output layer. Classic NN models recommend feed-forward algorithm which only passes the input data in one path, towards the output layer. Back-propagation is needed when there is an error signal produced at the output layer. Then the error is returned to preceding layers for reduction of error. It is performed by the weight update delta rule.

3.7 Functional Magnetic Resonance Imaging

Functional MRI is a category of imaging methods designed to illustrate regional and time-varying changes in brain metabolism [1]–[3]. fMRI's success stems from its proliferation, non-invasive appearance, reduced cost, and better spatial resolution. Progressively, fMRI is being used as a disease biomarker [8], [17] to monitor therapy [39] or to study pharmacological effectiveness [20]. It is therefore of interest to evaluate the mechanisms of contrast, the strengths and weaknesses and the evolutionary trends of this significant tool. As a brain imaging technique, fMRI has many major advantages: it is non-invasive and does not require radiation, making it safe for the patient, has excellent spatial and decent temporal resolution, as well as being easy to use for the experimenter.
fMRI works by identifying changes in blood oxygenation and ow that results in response to neuronal activity when a brain region becomes more active, it absorbs more oxygen and the blood flow increase to the active area to satisfy this increased demand. fMRI can be used to provide activation maps showing which brain parts are involved in a particular mental phase. Oxygen in capillary red blood cells is supplied to the neurons by hemoglobin. There is an increased demand for oxygen if the neuronal activity of the brain increases. And the local response is an increase in blood circulation regions with accelerated brain function. When oxygenated, hemoglobin becomes diamagnetic, but when de-oxygenated it becomes paramagnetic. Such variation in magnetic properties results in slight changes in the blood's MR signal depending on the degree of oxygenation. Since blood oxygenation differs based on the neuronal activity levels, these variations can be used to detect brain activity.

CNN has attracted much attention in recent years and has been commonly used in fMRI data processing, as relevant features can be extracted automatically [32], [37]. For example, CNN has been used to classify fMRI data effectively [32], and to identify and diagnose Alzheimer's disease (AD) and aMCI. The CNN method consists of the following three applications: feature extraction, auto-encoder construction, and 3D CNN construction. Restricted Boltzmann Machine (RBM) and Deep Boltzmann Machine (DBM) are also used to evaluate fMRI data, in addition to the commonly used methods mentioned above.

Chapter 4

Proposed Model

This chapter describes how we have followed our proposed system to implement for detecting Parkinson's Disease. Firstly, the specified data are amassed from the PPMI database. MRI images are typically acquired in slices one at a time. It can be sequentially or interleaved manner. Together the slices make up a 3D brain volume. The area is calculated from the current image and is fed as the input of the Convolutional neural network. Now the prediction model is obtained in which the subjects are tested for acquiring the desired result that whether the patient has PD or in the control stage.

4.1 Work Flow

A typical workflow to detect Parkinson's Disease is shown in figure 4.1.

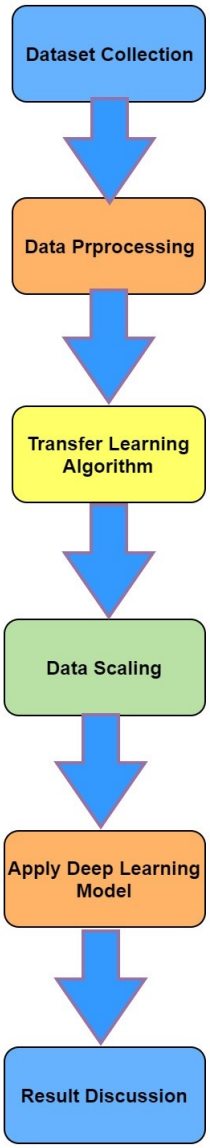

Figure 4.1: Figure of workflow

The above diagram shows the steps that we we will use to hit upon early signs and symptoms of Parkinson's disease. The fMRI records became collected from Parkinson's progression Markers Initiative (PPMI) database so that it will be used for detecting Parkinson;s Diasease.

4.2 Data Collection

The fMRI dataset is collected from the website of Parkinson's Progression Markers Initiative (PPMI). PPMI usually work on Parkinson's Disease and its prevention[33].

4.3 Data Pre-processing

In order to access the data faster and efficient way data preprocessing is necessary. The dataset contains total 604 people's fMRI data. Those data were mostly in NII file format some of them were in DCM file format. The detailed dataset description is presented in table and different graphs which are given below on table 4.1.

Table 4.1: Data formats of fMRI.

Data Format	Count of Data Format
DCM	16
NII	587

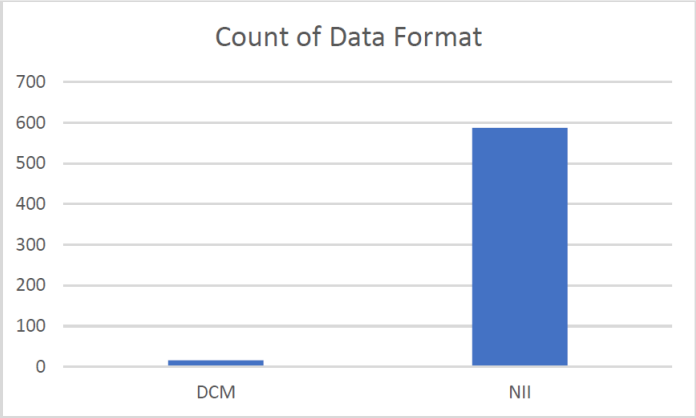

Figure 4.2: Data formats graph.

The bar chart of data format is given in figure 4.2.

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

Table 4.2: Different groups of PD from dataset.

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

There are 7 different groups in the dataset which is given in table in table 4.2 and figure 4.3 below. Most patient are in Phantom group which is an olfactory hallucination. This group's people smell an odor that is not actually there. This smell can be burned, foul, spoiled, or rotten. The other group is PD which means those

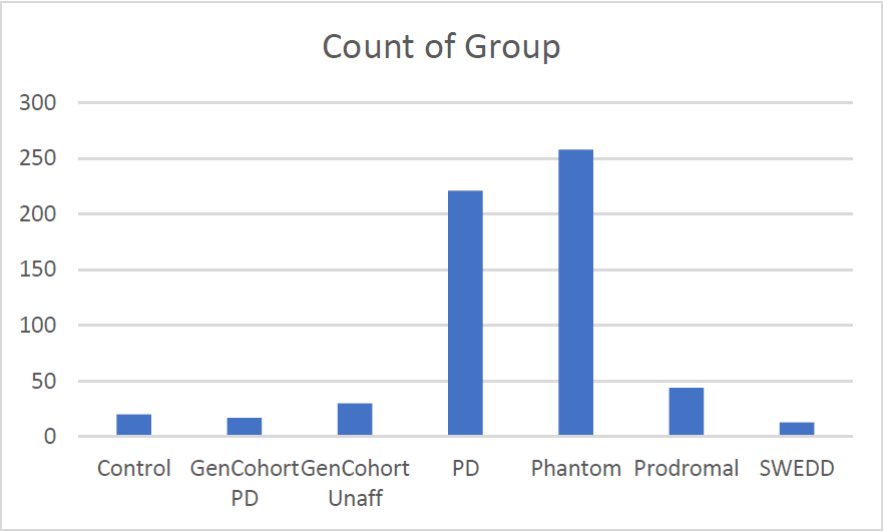

Figure 4.3: Different research group of dataset.

people who are this group are already affected in PD.

Table 4.3: Gender of patients of dataset.

Sex	Count
Male	131
Female	258
Unknown	214

There were male, female and x indicates the unknown gender in the dataset given in figure 4.4.

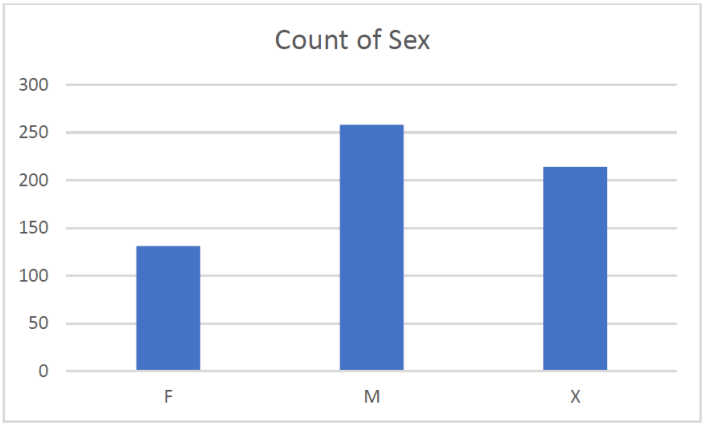

Figure 4.4: Gender description of dataset.

Parkinson's Disease affected people are mostly above 40 years and very few are below than this given in figure 4.5.

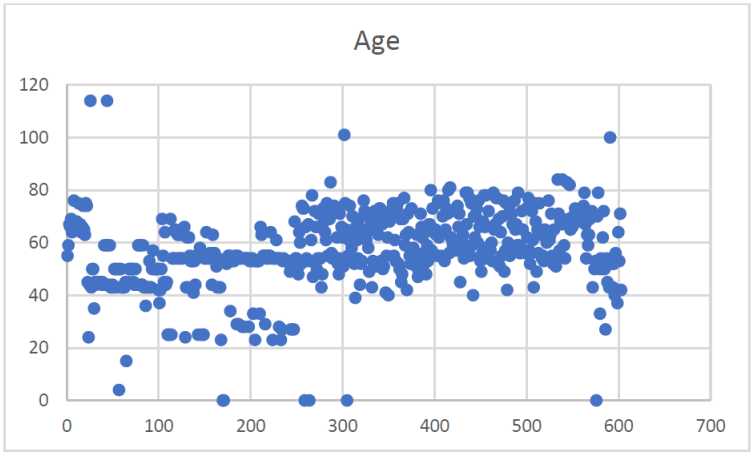

Figure 4.5: Scatter diagram of the range of ages of different research people.

Table 4.4: Different states of patients of dataset.

Description	Count of Description
ep2d_bold_rest	52
ep2d_RESTING_STATE	551

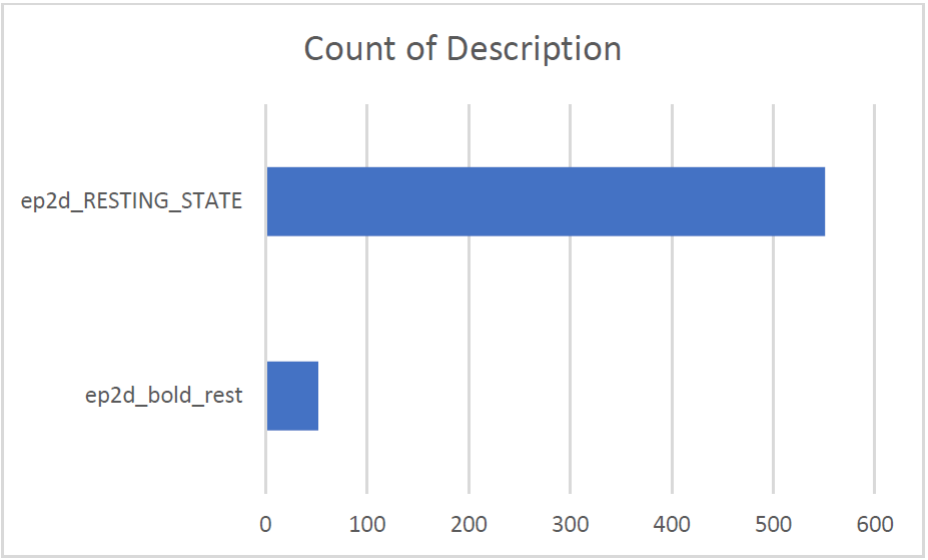

Figure 4.6: Different states of patients.

There are two states in the fMRI data. They are resting state and BOLD state given in figure 4.6.

These data are preprocessed for generating time series of voxels. MRI images are typically acquired in slices one at a time. It can be sequentially or interleaved manner. Together the slices make up a 3D brain volume. The thickness of each slice may contain up to 192mm.

Experiment studies many subjects where the subject is usually PD affected and non-affected person. Each subject may be scanned during multiple sessions. Each

session consists a several runs. Each run consists of a series of brain volumes. Each volume is made up of multiple slices. Each slice contains many voxels. Each voxel has an intensity associate with it. In a 64*64 matrix there is 192/64=3mm voxel.

4.4 Data Extraction and Processing

First of all, the Parkinson's disease affected people and non-affected people were separated from our dataset that we collected from the website of Parkinson's Progression Markers Initiative (PPMI). The fMRI images are acquired one slice at a time; therefore, not all volumes of the image were acquired at the same time. The Parkinson's disease affected people were named PD, non-affected people were named Control and others are named GenCohort PD, GenCohortUnaff, Phantom, Prodromal and SWEDD and created a csv file format using python libraries. From these different types of groups, we compared PD and non-PD subjects by analyzing the patient's data of different times of months or years from the dataset. For data training class, we have used 800 slices from both subject group and we have used 800 slices more for testing class. Finally, we have applied different CNN models for our classification process. We have used three architectures of CNN and they are - VGG19, VGG16 and InceptionV3.

4.5 Convolutional Neural Networks

Convolutional Neural Networks (CNN) are one of the famous Deep artificial Neural Networks. CNNs are made from learnable weights and biases. CNNs are frequently used in image recognition, image clustering and classification, object detection, etc. CNNs use rather less preprocessing when compared with other algorithms of image processing. Any images of particular locales are passed through the convolutional layers and appear the ultimate detection result. This demonstrates incorporates a few layers named The Bit, Pooling and the Completely Associated Layer (FC Layer) through which numerous pictures or districts are trained by nourishing them into the network [25].

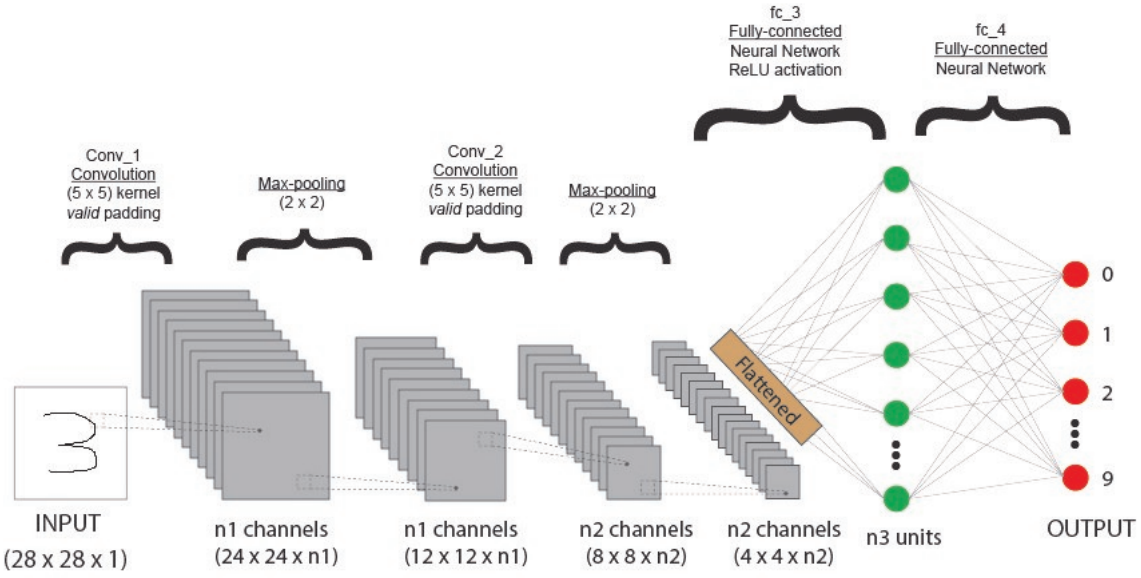

Figure 4.7: Convolutional Neural Network.

Here Figure 4.7 represents the layer of convolutional neural networks. Any images with specific bounding boxes are passed through these layers. The primary layer is the Kernel which represents the image in a lattice of 5 x 5 x 1. At that point utilizing the second layer which is Valid Padding increments the dimensionality of the image. Then Pooling Layer diminishes the estimate of the assessed Include. Fully-Connected layer then presents the last output of the required image.

4.5.1 Reasons of Using CNN

Whereas neural networks have been around for the past 50 a long time, there have been critical advancements within the zone of convolutional neural networks within the later past. This section covers the points of interest of utilizing CNN for image recognition.

Feature Learning:

The main feature of CNNs is the feature learning. The utilization of CNNs are propelled by the reality that they can memorize pertinent.

Weight Sharing:

Shared weights essentially imply that the same weights is utilized for two layers within the demonstrate. This fundamentally implies that the same parameters will be utilized to represent two distinctive transformations within the framework. This can be fundamentally implying the same lattice components may be overhauled different times amid back proliferation from varied gradients. The same set of components will encourage changes at more than one layer rather than those from a single layer as conventional neural network.

Execution Term:

CNNs beat NNs on conventional picture acknowledgment assignments and various another task. For occasion, we utilized VGG19, VGG16 and Initiation on our dataset.

New Problem:

For solving a completely new difficulty CNNs are exceptionally great highlight mechanism. This implies merely can extricate valuable properties from an as of now prepared CNN with its prepared weights by bolstering your information on each step and tune the CNN a bit for the particular assignment. For example, Include a classifier after the final layer with names particular to the assignment. Usually too called pre-training and in this works CNNs are exceptionally effective compared to NNs.

Ruggedness and distortion in the image

Discovery utilizing CNN is tough to twists such as alter in shape due to camera focal point, diverse lighting conditions, different postures, nearness of fractional occlusions, flat and vertical shifts, etc. In any case, CNNs are shift-invariant since the same weight configuration is utilized over space. In hypothesis, we too can accomplish move invariants using completely associated layers. But the result of preparing, in this case, is different units with indistinguishable weight patterns at diverse areas of the input. To memorize these weight setups, an expansive number of training instances would be required to cover the space of conceivable varieties.

Easier and better in terms of training

Easier and better in terms of training Once more utilizing the standard neural network that would be proportionate to a CNN, since the amount of parameters would be much higher, the preparing time would moreover increment proportionately. In a CNN, since the amount of parameters is radically diminished, preparing time is proportionately diminished. Too, expecting culminate preparation, we can plan a standard neural arrange whose execution would be the same as a CNN. But in commonsense training, a standard neural arrange proportionate to CNN would have to a greater extent parameters, which would conduct to more scrunch addition amid the preparing handle. Thus, the execution of a standard neural arrangement comparable to a CNN will continuously be hapless.

4.5.2 Different CNN Architechtures

We have used three CNN architecture on our PPMI dataset which are VGG19, VGG16 and InceptionV3 for classfification.

VGG Architecture

We have utilized VGG in numerous deep learning image classification problems and we have compared the accuracy with other CNN architectures [68].

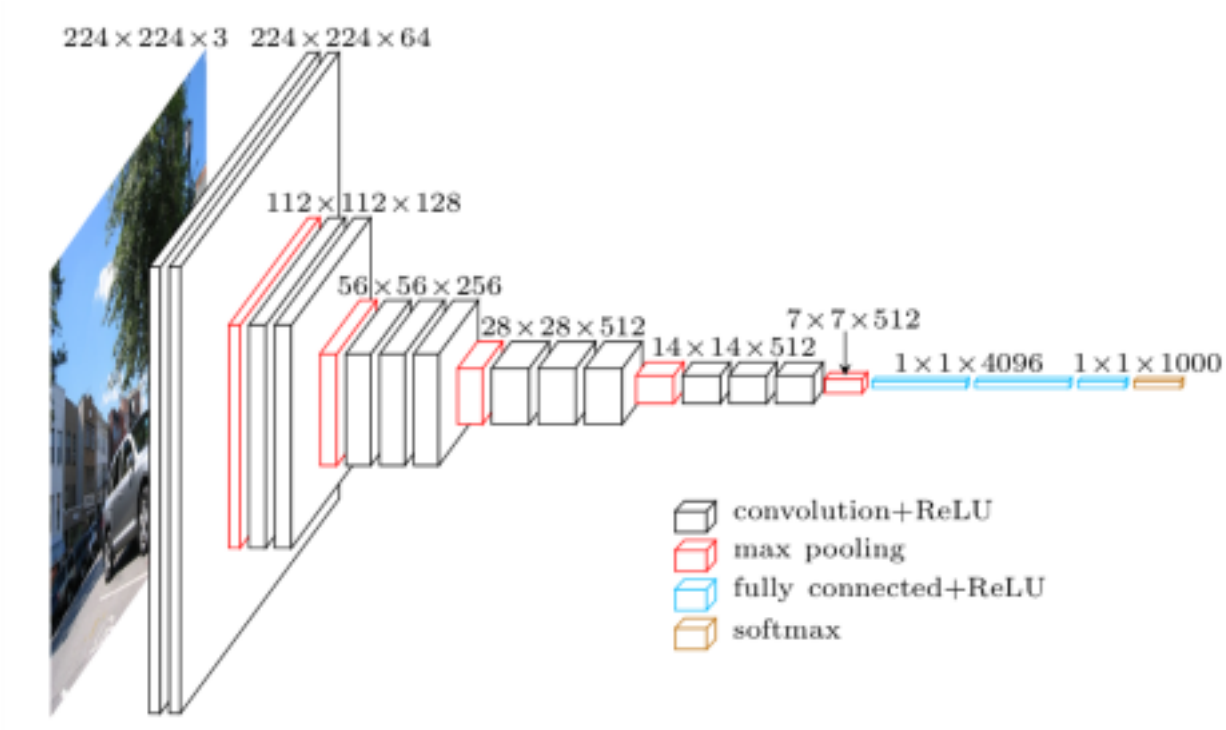

Figure 4.8: VGG architecture.

Figure 4.8 represents the architecture view of VGG.This network is characterized by using its straightforwardness, using best 33 convolutional layers stacked on best of every other in expanding intensity. Lessening quantity measure is treated by

way of max pooling. Two fully-connected layers, every with 4,096 nodes are at that point taken after via a softmax classifier (above). The "16" and "19" stand for the wide variety of weight layers within the network (columns D and E in figure 4.9):

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Figure 4.9: Table of Deep CNNs for Large Scale Image Recognition.

Due to its depth and number of fully-connected nodes, VGG is over 533MB for VGG16 and 574MB for VGG19. This makes sending VGG a tedious task.

Inception Architecture

InceptionV3 may be a convolutionary neural network, trained from the ImageNet information on over 1,000,000 pictures.

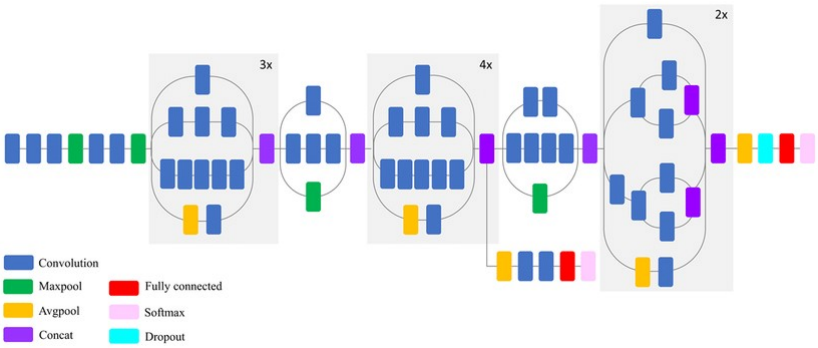

Figure 4.10: InceptionV3 Architecture.

Figure 4.10, The picture scale of the Network is 299-by-2. The objective of the beginning module is to behave as a "multi-level feature extractor" by way of computing 11, 33, and 55 convolutions inside the identical module of the network — the yield of these filters are at that point stacked alongside the channel measurement and sometime recently being bolstered into the subsequent layer in the network.

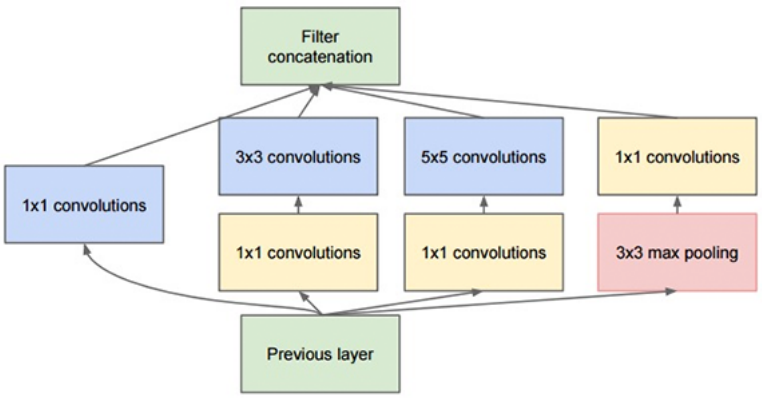

Figure 4.11: Inception module.

In figure 4.11, Inception module is shown which represents the layers of inception module.

4.5.3 Choosing Activation Function

The activation function does the non-linear change to the input making it competent to learn and perform more complex errands.

ReLu

In case of employing a step work our classification would have been a straight one. As our data is nonlinear which implies, we will effectively backpropagate the errors and have numerous layers of neurons, we have utilized the ReLu activation function

in mid-layer. The rectified linear activation is the default activation when creating multilayer Perceptron and CNN.

It transforms the linear form into a non-linear form.It is used in hidden layer to generate testing accuracy. It can be represented as,

$$f(x) = max(0, x)$$

It sets anything less than or equal to 0 (negative numbers) to be 0 and it keeps all the same values for any values > 0.

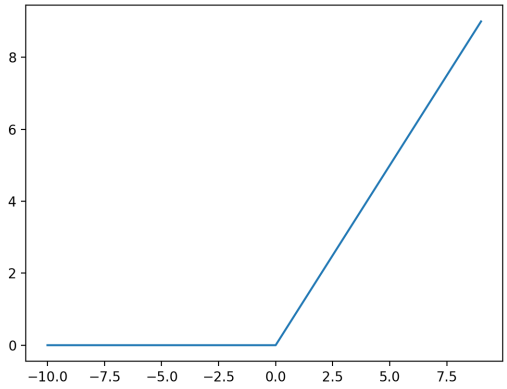

Figure 4.12: ReLu curve.

We can see from the above figure 4.12, the ReLU curve, and the function we used to represent our prediction model. Another reason for using ReLu is it overcomes the vanishing slope issue, permitting models to learn faster and perform better and make a significant distinction to the accuracy.

Softmax
We have used the softmax activation function in the output layer as we're making a neural network for binary classification problems and testing accuracy purpose.

Softmax activation function comes about in a multiclass probability distribution over your target classes. Numerically the softmax function is appeared underneath, where z i the inputs to the output layer (on the off chance that you've got 10 output units, at that point there are 10 components in z). And once more, j files the output units, so j = 1, 2, ..., K.

$f_j(z) = \frac{e^j j}{\sum_k e^z k}$

4.5.4 Cost function

As we've got a thousand samples in our dataset, so we may need to utilize all the samples for completing one iteration whereas performing the Gradient Descent and it has got to be done for each iteration until the minima is come to. A standard strategy is gradient descent, which can be depicted by the taking after update rule

for t = 1, 2, . . .
$w(t) = w(t1)tP(w(t1)) = w(t1)tnXni = 1i(w(t1))...(1)$
Subsequently, it gets to be computationally exceptionally costly to perform. This issue is unraveled by Stochastic Gradient Descent. A popular alteration is stochastic gradient descent (SGD):
where at each iteration t = 1, 2, . . ., we draw it haphazardly from 1, . . . n, and

$w(t) = w(t1)\eta t\psi it(w(t1))...(2)$
The desire $E[w(t)|w(t1)]$ is indistinguishable to (1).
A more common adaptation of SGD is the following
$w(t) = w(t1)\eta tgt(w(t1), \xi t)...(3)$
where ξt is a irregular variable which will depend on
w (t1), and the desire (with regard to
ξ t) E[gt(w (t1), $\xi t)|w(t1)] = P(w(t1))$.

We used adam optimizer which is an evolved version of stochastic gradient descent with epsilon 0.0001 at a learning rate $1e^{-}5$ is used to train the network for optimum accuracy. Adam [26] is a versatile algorithm that optimizes the learning rate and it has been designed in a way that it can prepare deep neural networks.

4.5.5 Loss function

Neural networks are prepared to utilize stochastic gradient descent and require that we need a loss function to plan and design our worked model. Categorical Cross

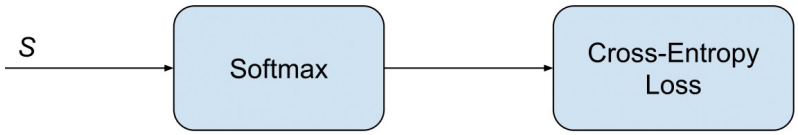

Figure 4.13: Cross entropy.

entropy loss function has applied for make a balance on data.It is used for multi-class classification for optimizing classifcation models.The value between 0 and 1 and helps to calculating probability difference in machine learning. The equation for cross section is given below,

$CE = -\sum_j^C t_i log(f(s)_i)$

4.5.6 Feature Extraction

There are two primary parts in a common CNN architecture for image classification. One is “feature extractor” that is based on convolution layers, and “classifier” which as a rule-based on completely connected layers. To extract features from CNN models we have used VGG19, VGG16 and InceptionV3 on our datasets. And here, CNN worked as a dynamic extractor.

Chapter 5

Implementation and Result Analysis

5.1 Implementation

After processing the dataset, we have passed 800 MRI slices to the different CNN architectures for training the prediction model and the rest 800 slices were utilized to test the accuracy. Some of the slices are given below in(figure 5.3).

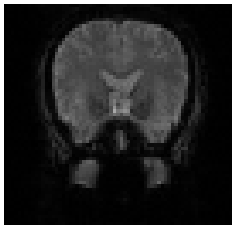

Figure 5.1: (a)

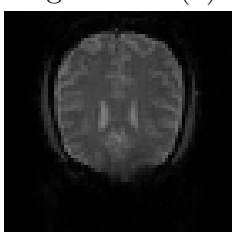

Figure 5.2: (a)

Figure 5.3: MRI slices of patients.

We have got these MRI slices after splitting the dataset.Then we have passed them directly to VGG19, VGG16 and InceptionV3 models for classification to detect Parkinson's Disease.After classification using three CNN architechtures we got some result and later we have analyzed those result.

5.2 Result

We have calculated the accuracy by using an epoch of 1, 5, 8, 10, 15, 18 and 20. Within 20 epoch we have got almost ninety percent accuracy.

5.2.1 Accuracy for VGG19

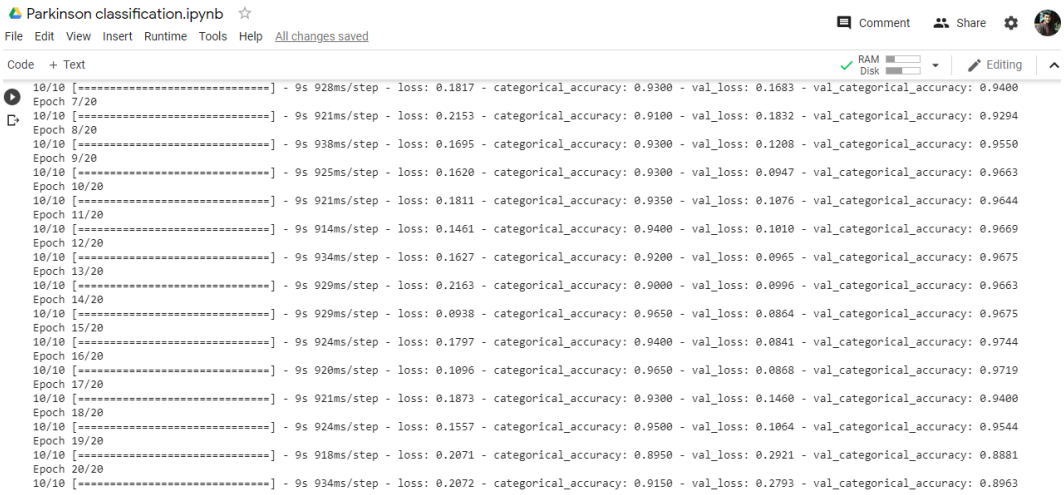

Figure 5.4: Accuracy for VGG19.

Here, we can see from the avobe figure 5.4 that when we run total 20 epochs in VGG19 architecture for training, we get about 90% accuracy from this model at 20th epoch.

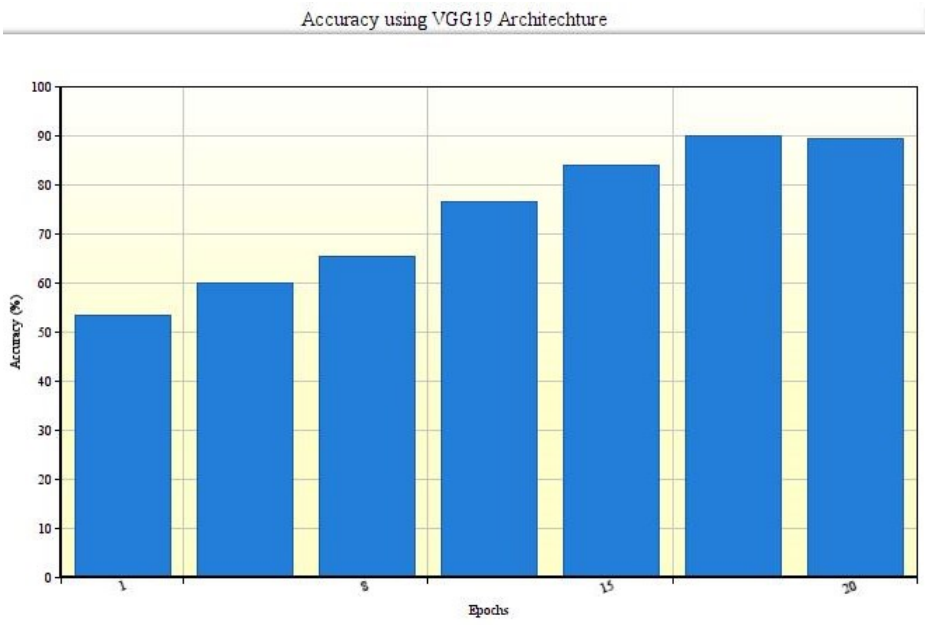

Figure 5.5: Bar graph of accuracy for VGG19.

Within the figure 5.5, we found the exactness of detecting Parkinson's disease when employing a convolutional neural network's architecture VGG19. We run 20 epochs

in VGG19. We got an accuracy for each epoch. Whereas running the 1st epoch the accuracy we got was as it were 55.5%. At the 10th epoch it expanded to 70.5% Essentially on the encourage ages the accuracy expanded. The most elevated accuracy we were able to obtain at 20th epoch was 91.5% whereas utilizing VGG19.

5.2.2 Accuracy for VGG16

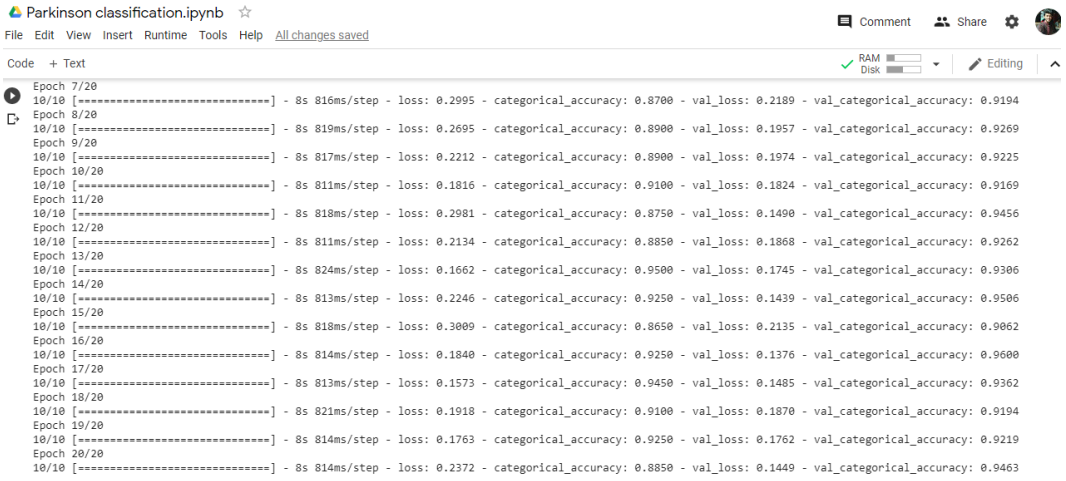

Figure 5.6: Accuracy for VGG16.

Here also, we can see from the figure 5.6 shown in below that when we run total 20 epochs in VGG16 architcture for training, we get about 89% accuracy from this model at 20th epoch.

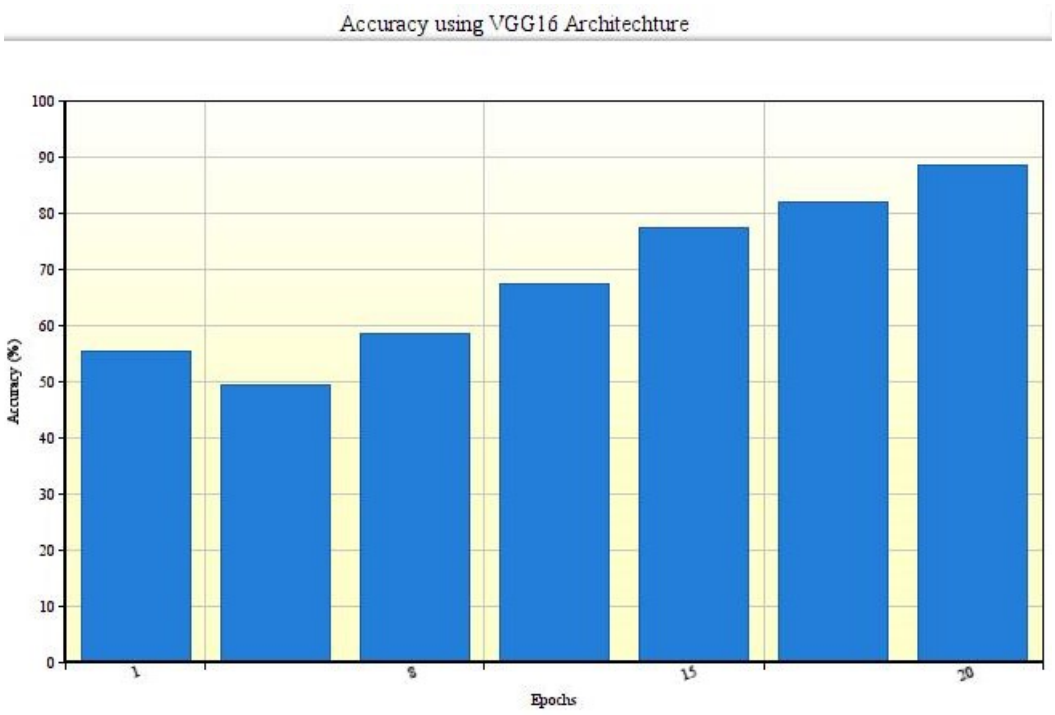

Figure 5.7: Bar graph of accuracy for VGG16.

Within the figure 5.7, we have found the precision of detecting a Parkinson's disease when employing a convolutional neural network's architecture VGG16. Essentially, we run 20 epochs in VGG16 as well. Whereas running the 1st epoch the exactness for detecting the Parkinson's disease was 55.5%. While running the 10th epoch we were able to induce the exactness up to 67.5%.And the highest accuracy we might get whereas utilizing VGG16 was 88.5% which was within the 20th epoch.

5.2.3 Accuracy for InceptionV3

```
10/10 [==============================] - 9s 912ms/step - loss: 0.2023 - categorical_accuracy: 0.9050 - val_loss: 0.1348 - val_categorical_accuracy: 0.9413
Epoch 7/20
10/10 [==============================] - 9s 912ms/step - loss: 0.1947 - categorical_accuracy: 0.9250 - val_loss: 0.1452 - val_categorical_accuracy: 0.9425
Epoch 8/20
10/10 [==============================] - 9s 922ms/step - loss: 0.1629 - categorical_accuracy: 0.9350 - val_loss: 0.1509 - val_categorical_accuracy: 0.9406
Epoch 9/20
10/10 [==============================] - 9s 917ms/step - loss: 0.2058 - categorical_accuracy: 0.9250 - val_loss: 0.1510 - val_categorical_accuracy: 0.9369
Epoch 10/20
10/10 [==============================] - 9s 922ms/step - loss: 0.2210 - categorical_accuracy: 0.8950 - val_loss: 0.1294 - val_categorical_accuracy: 0.9450
Epoch 11/20
10/10 [==============================] - 9s 946ms/step - loss: 0.2128 - categorical_accuracy: 0.9150 - val_loss: 0.1359 - val_categorical_accuracy: 0.9388
Epoch 12/20
10/10 [==============================] - 9s 923ms/step - loss: 0.1464 - categorical_accuracy: 0.9400 - val_loss: 0.1082 - val_categorical_accuracy: 0.9525
Epoch 13/20
10/10 [==============================] - 9s 918ms/step - loss: 0.1599 - categorical_accuracy: 0.9300 - val_loss: 0.1272 - val_categorical_accuracy: 0.9469
Epoch 14/20
10/10 [==============================] - 9s 926ms/step - loss: 0.2066 - categorical_accuracy: 0.9050 - val_loss: 0.1213 - val_categorical_accuracy: 0.9475
Epoch 15/20
10/10 [==============================] - 9s 925ms/step - loss: 0.1995 - categorical_accuracy: 0.9100 - val_loss: 0.2135 - val_categorical_accuracy: 0.9038
Epoch 16/20
10/10 [==============================] - 9s 922ms/step - loss: 0.1735 - categorical_accuracy: 0.9200 - val_loss: 0.1680 - val_categorical_accuracy: 0.9362
Epoch 17/20
10/10 [==============================] - 9s 914ms/step - loss: 0.2764 - categorical_accuracy: 0.8800 - val_loss: 0.1423 - val_categorical_accuracy: 0.9394
Epoch 18/20
10/10 [==============================] - 9s 917ms/step - loss: 0.2214 - categorical_accuracy: 0.9050 - val_loss: 0.1096 - val_categorical_accuracy: 0.9506
Epoch 19/20
10/10 [==============================] - 9s 908ms/step - loss: 0.1716 - categorical_accuracy: 0.9150 - val_loss: 0.0862 - val_categorical_accuracy: 0.9700
Epoch 20/20
10/10 [==============================] - 9s 920ms/step - loss: 0.2208 - categorical_accuracy: 0.8950 - val_loss: 0.1448 - val_categorical_accuracy: 0.9400
```

Figure 5.8: Accuracy for InceptionV3.

Here also, we can see from the avobe figure 5.8, that when we run total 20 epochs in InceptionV3 architcture for training, we get about 89% accuracy from this model at 20th epoch.

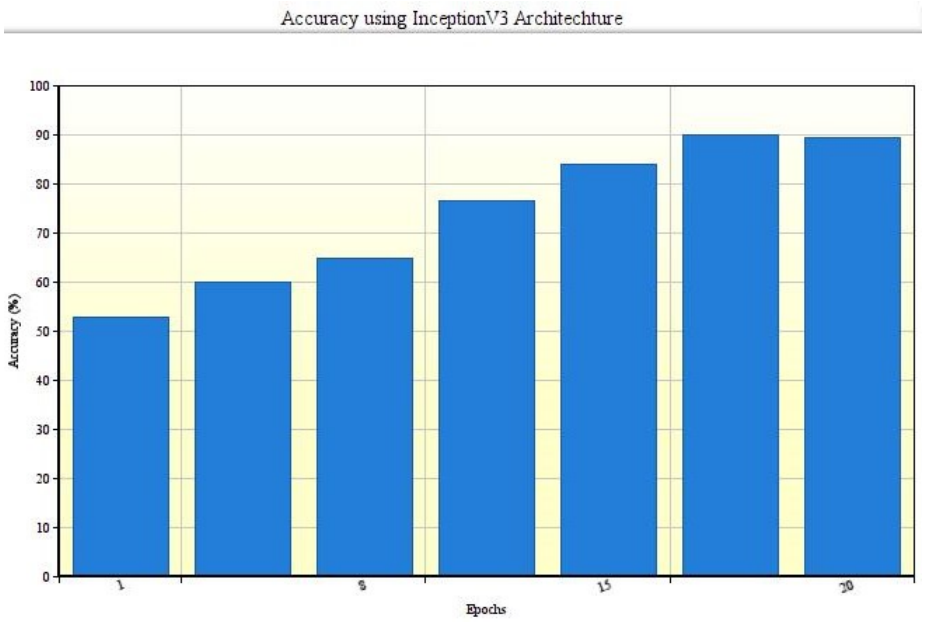

Figure 5.9: Bar graph of accuracy for InceptionV3.

Within the figure 5.9, we have found the precision of detecting a Parkinson's disease when employing a convolutional neural network's architecture InceptionV3. So also, we run 20 epochs in InceptionV3 as well. Running the 1st epoch, we got the precision of 53.0% for the location of Parkinson's disease. The accuracy drastically increased within the 10th epoch to 76.5%. After further running the epochs at the 20th epoch we were able to obtain the most noteworthy exactness of 89.5%.

5.2.4 Loss Function

Loss function makes a difference in optimizing the parameters of the neural networks to decrease the loss for a neural network. The loss is calculated using loss function through matching the actual value and predicted cost through a neural network.The loss values are given in below graphs:

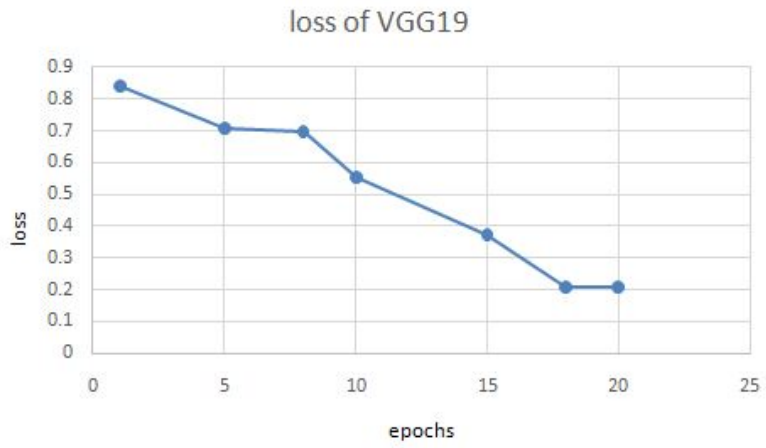

Figure 5.10: Loss values for VGG19 loss model.

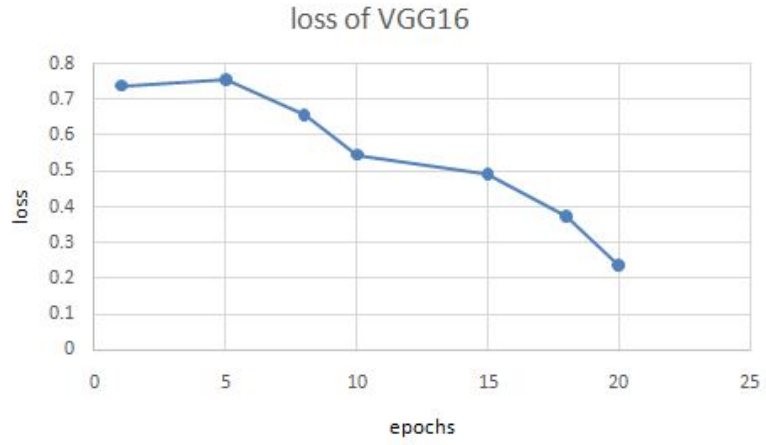

Figure 5.11: Loss values for VGG16 loss model.

Within the figure 5.10, 5.11, 5.12, we will see the loss values of the VGG19, VGG16 and InceptionV3 model.As we will see from the graph, within the 1st epochs we find 0.8397 for VGG19, 0.7409 for VGG16 and 0.7574 for InceptionV3. So, we can say VGG19 is the most exceedingly bad in the case of 1st epoch as we get 0.8397 for VGG19.In the 10th epoch we find loss for VGG19 is 0.5509,for VGG16 is 0.5462 and for Inceptionv3 is 0.3759. Within the 20th epoch we find loss value for VGG19 is 0.2072,for VGG16 is 0.2372 and for InceptionV3 is 0.2208. Within the 20th epochs we can see that we get lowest loss value for VGG19 architecture.

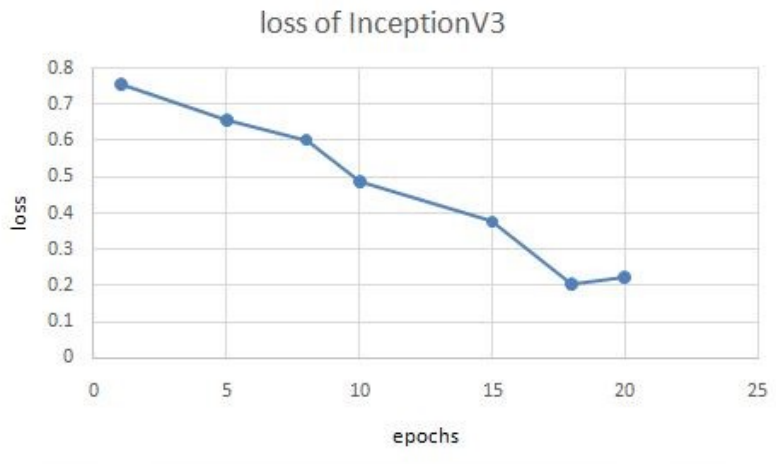

Figure 5.12: Loss values for InceptionV3 loss model.

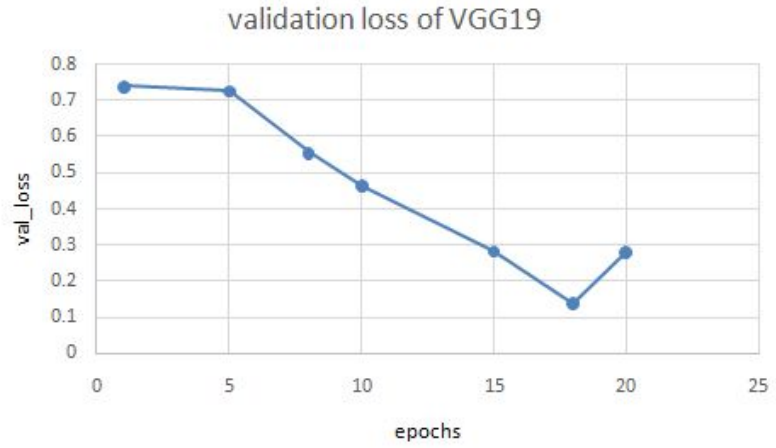

Figure 5.13: Validation Loss values for vgg19 model.

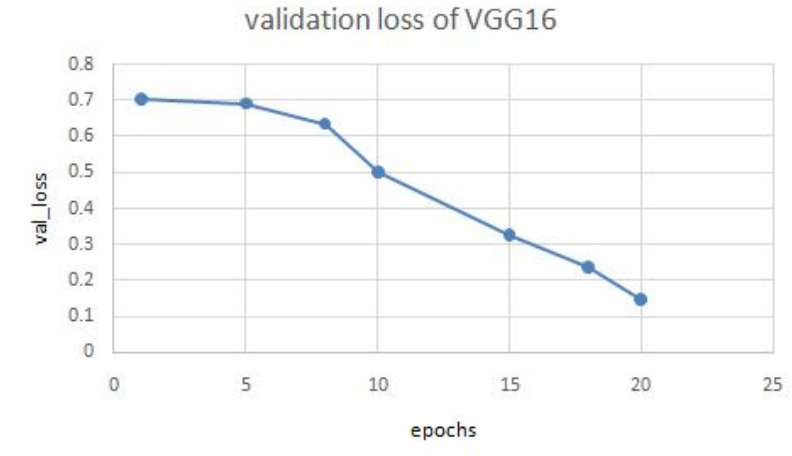

Figure 5.14: Validation Loss values for vgg16 model.

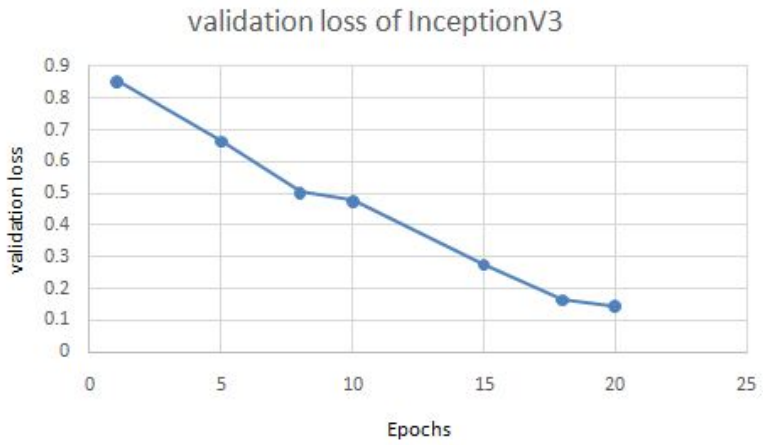

Figure 5.15: Validation Loss values for inceptionV3 model.

Within the figure 5.13, 5.14, 5.15 we will see the validation loss values of the VGG19, VGG16 and InceptionV3 model.As we will see from the graph, within the 1st epochs we find validation loss 0.741 for VGG19, 0.7042 for VGG16 and 0.8549 for InceptionV3. So, we can say InceptionV3 is the most exceedingly bad in the case of 1st epoch as we get 0.8549 for InceptionV3.In the 10th epoch we find loss for VGG19 is 0.4631, for VGG16 is 0.5003 and for Inceptionv3 is 0.4769. Within the 20th epoch we find loss value for VGG19 is 0.2793,for VGG16 is 0.1449 and for InceptionV3 is 0.1448. Within the 20th epochs we can see that we get lowest validation loss value for InceptionV3 architecture.

5.3 Discussion

Table 5.1: Table of between accuracy of different CNN architecture

Epochs	Accuracy (%)of different architecture		
	VGG19	VGG16	InceptionV3
1	45.5	55.5	53
5	59.5	49.5	60
8	55.5	58.5	65
10	70.5	67.5	76.5
15	80	77.5	84
18	92.5	82	90
20	91.5	88.5	89.5

This Table 5.1 has been created to show the highest value of each epoch. Each epoch had a highest accuracy value. Those highest values were inserted in Table 5.1 to have a clear view of the whole result altogether.

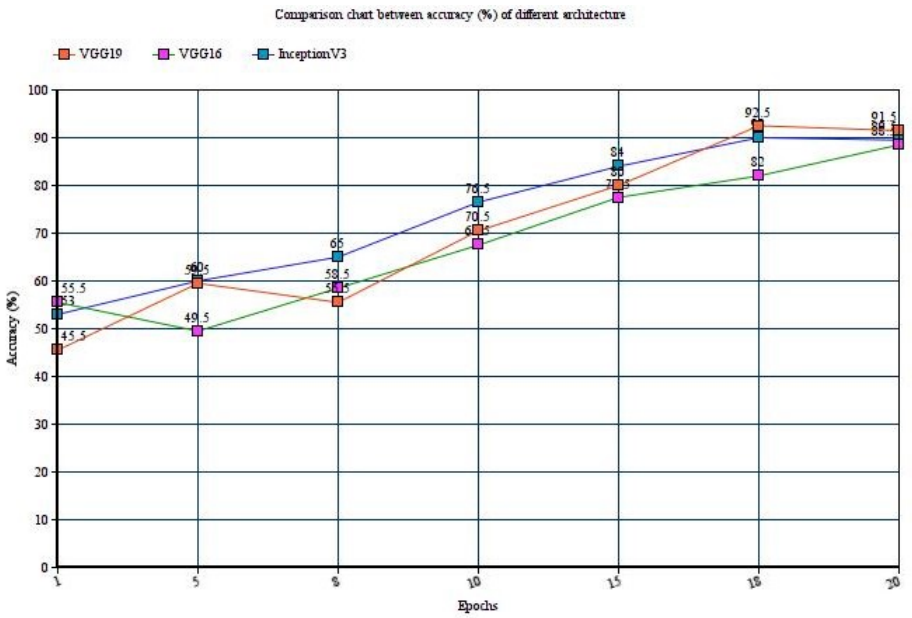

Figure 5.16: Comparison between accuracy of different CNN architectures.

In the Figure 5.16 we can see the comparison between the VGG19, VGG16 and InceptionV3. We took the highest accuracy of an epoch and plot it. Accuracy varies from each architecture. As we can see from the graph, in the 1st epoch VGG19 give an epoch accuracy of 45.5%, the VGG16 give an epoch accuracy of 55.5% lastly InceptionV3 gives an epoch accuracy of 53%. So, we can say VGG19 is the worst in case of 1st epoch. In the 5th epoch the highest accuracy from running the epoch we get for VGG19 in 56.55%, for VGG16 is 49.5% and for InceptionV3 we get 60.0%. In the 8th epoch VGG19, VGG16 and InceptionV3 give accuracy respectively 54.5%, 58.5% 65%. Then from epoch 10 we get accuracy 70.5%, 68.5% 76.5% from VGG19,

VGG16 and InceptionV3 respectively. 15th epoch give accuracy of 80%, 78.5% 84% from VGG19, VGG16 and InceptionV3 respectively. In 18th epoch VGG19, VGG16 and InceptionV3 give accuracy of 92.5%, 82% 80.5% respectively. Lastly for the 20th epoch we can see the highest epoch accuracy for VGG19 is 91.5%, for VGG16 is 88.5% and for InceptionV3 the highest epoch accuracy is 89.5%. So, in the 20th epoch the highest epoch accuracy between the three architecture VGG19 has the highest epoch accuracy. The highest epoch accuracy we have acquired from all the three architecture is 91.5% which is obtained from VGG19.

Table 5.2: Table of validation accuracy of different architecture.

Epochs	Validation accuracy(%) of different architecture		
	VGG19	VGG16	InceptionV3
1	50	50.25	50.25
5	50	50.88	52.69
8	74.75	60.75	76.06
10	76	77.06	76.38
15	89.63	88.31	88.31
18	96.19	92.81	93.37
20	96.63	94.63	94

This Table 5.2 shows the validation accuracy of all the architectures. These are the ultimate validation accuracy after each epoch.

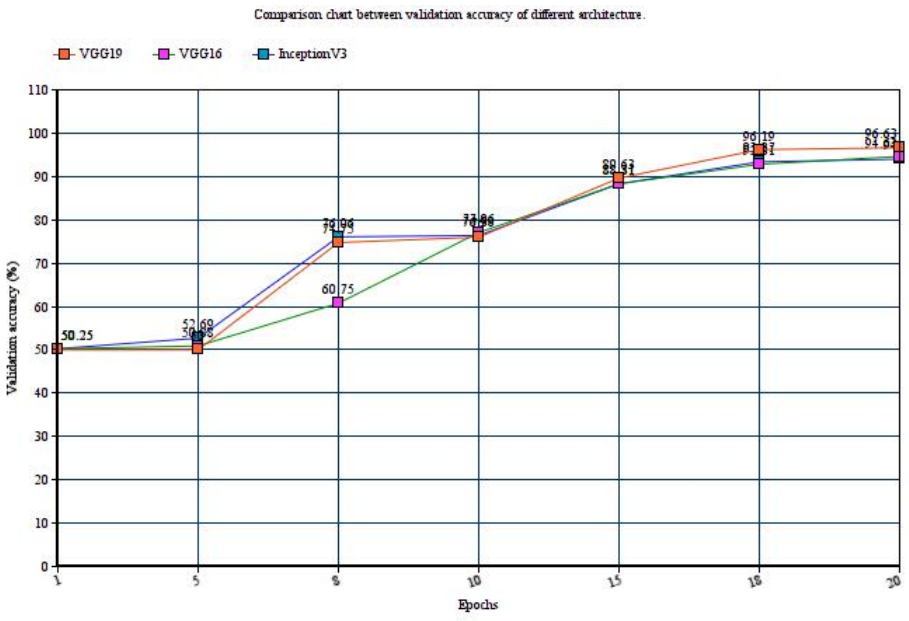

Figure 5.17: Comparison between validation accuracy of different CNN architectures.

In the Figure 5.17, we can see the comparison of validation accuracy between the VGG19, VGG16 and InceptionV3. We took the highest accuracy of an epoch and

plot it. Accuracy varies from each architecture. As we can see from the graph, in the 1st epoch VGG19 give an epoch accuracy of 50%, the VGG16 give an epoch accuracy of 50.25% lastly InceptionV3 gives an epoch accuracy of 50.25%. So, we can say VGG19 is the worst in case of 1st epoch. In the 5th epoch the highest accuracy from running the epoch we get for VGG19 in 50%, for VGG16 is 50.88% and for InceptionV3 we get 52.69%. In the 8th epoch VGG19, VGG16 and InceptionV3 give accuracy respectively 74.75%, 60.75% 76.06%. Then from epoch 10 we get accuracy 76%, 77.06% 76.38% from VGG19, VGG16 and InceptionV3 respectively. 15th epoch give accuracy of 89.63%, 88.31% 88.31% from VGG19, VGG16 and InceptionV3 respectively. In 18th epoch VGG19, VGG16 and InceptionV3 give accuracy of 96.19%, 92.81% 93.37% respectively. Lastly for the 20th epoch we can see the highest epoch accuracy for VGG19 is 96.63%, for VGG16 is 94.63% and for InceptionV3 the highest epoch accuracy is 94%. So, in the 20th epoch the highest epoch accuracy between the three architecture VGG19 has the highest epoch accuracy. The highest epoch accuracy we have acquired from all the three architecture is 96.63% which is obtained from VGG19.

Table 5.3: Table of loss values of different architecture.

Epochs	Loss values of different architecture		
	VGG19	VGG16	InceptionV3
1	0.8397	0.7409	0.7574
5	0.7075	0.7575	0.6562
8	0.6942	0.6563	0.6023
10	0.5509	0.5462	0.4886
15	0.3723	0.4935	0.3759
18	0.2066	0.3758	0.2025
20	0.2072	0.2372	0.2208

The loss function of all the architectures are shown in this Table 5.3. These are the final loss function after the finishing of each epoch. As we can see that the loss function generated from these architectures are quite high at the beginning. The loss function decreases after each epoch. The graph shown on Figure 5.18, displays Loss Function with respect to Epoch number. Generally, the loss function of the epoch gradually decreases. As we can see in the VGG16 line, the line went down and then gradually went up. However, it decreased a lot in the end. Same goes for the VGG19 and inception architecture. In these architectures. Here VGG19 gives minimum loss function value and VGG16 gives maximum value of loss function compares to other architecture. As we know, lower error on the dataset means the lowest test loss and highest testing accuracy. Thus, VGG19 produced the highest accuracy with the lowest test loss function.

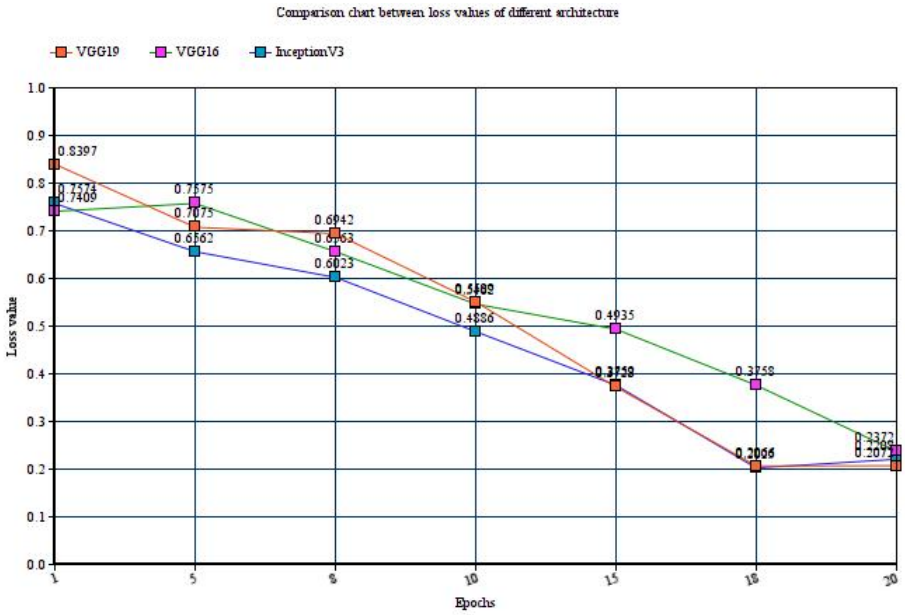

Figure 5.18: Comparison between loss values of different CNN architectures.

Comparison between accuracy of different CNN Architectures:

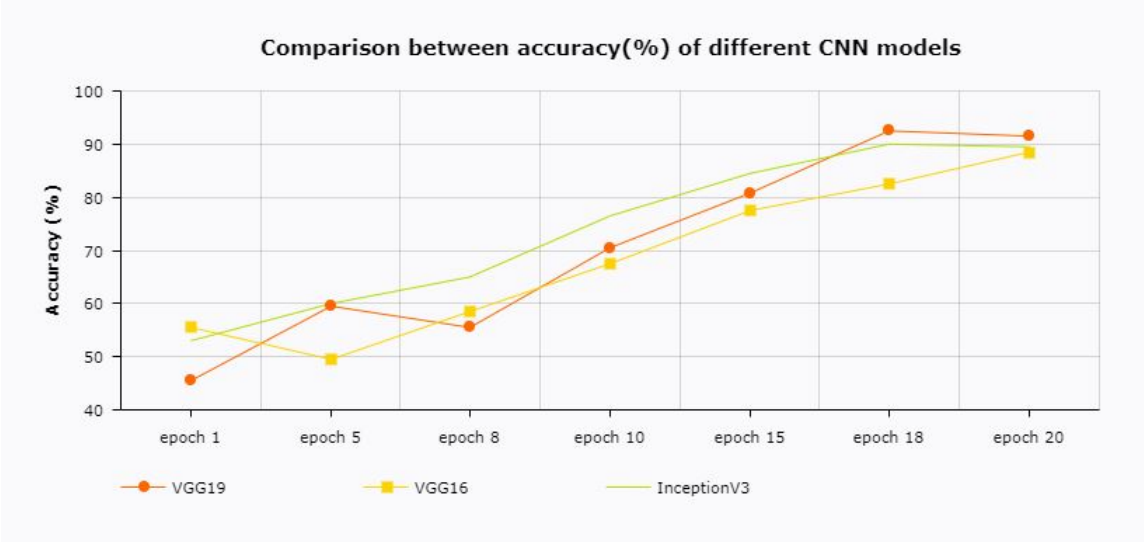

Figure 5.19: Comparison between accuracy of different CNN architectures.

Finally within figure 5.19 and figure 5.20 we can see the comparison between the VGG19, VGG16 and InceptionV3. We took the highest accuracy of an epoch and plot it. Exactness shifts from each architecture. As we will see from the graph, within the 1st epochs VGG19 gives a precision of 45.5%, the VGG16 allows a precision of 55.5% in conclusion InceptionV3 gives an exactness of 53.0%. So, we can say VGG19 is the most exceedingly bad in the case of 1st epoch. in the 2nd epoch the most noteworthy exactness from running the epoch 10 time we get for VGG19 in 70.5%, for VGG16 is 67.5% and for InceptionV3 we get 76.5%. Within the 10th epochs InceptionV3 has the most elevated precision of 76.5%. Besides, within the

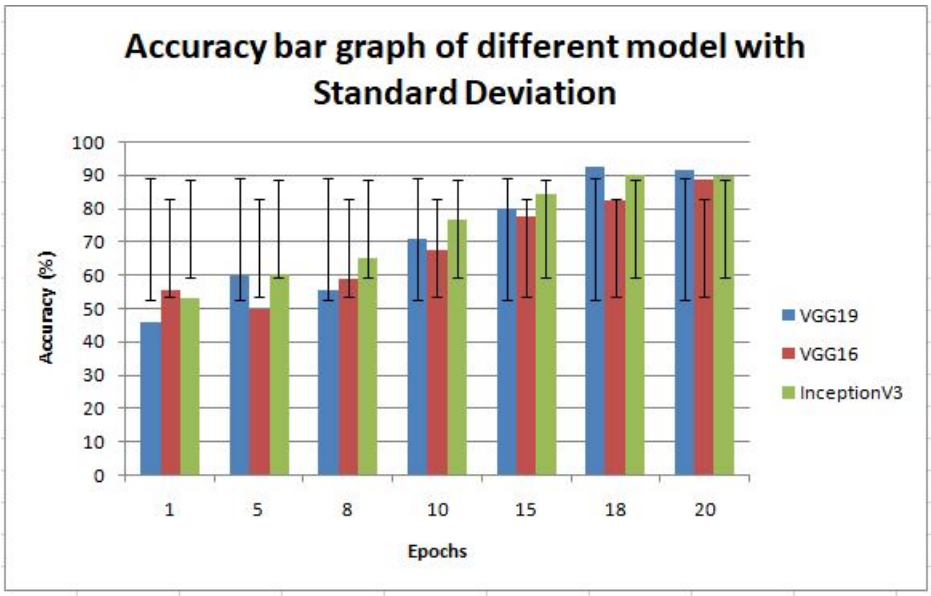

Figure 5.20: Accuracy bar graph of different model with Standard Deviation.

15th epoch the highest exactness for running the epoch 15 times we get the most elevated precision for VGG19 is 80.0%, for VGG16 in 77.5% and InceptionV3 84.5%. Here InceptionV3 has the most noteworthy accuracy. Within the 20th epochs we can see that the accuracy expanded apart. Like for VGG16 the most elevated accuracy is 88.5%, for VGG19 model the highest precision is 91.5%.
Thus we can make the final decission is that VGG19 model gives the best performance and accuracy in this research on detecting Parkinson's Disease.

Chapter 6

Conclusion

The primary purpose of the thesis work is to categorize patients with comparisons of different classifiers who have been affected by PD based on their neuro-image. The principal cause of choosing this topic was that it is difficult to analyze the disease, particularly at its prior stages. With this proposed prediction model, we aim to make it simpler for doctors to do exact determination and prediction of PD. We isolated the work of detection and prediction strategies to distinguish and measure the region of the brain that is affected because of PD, and use that information in a neural network to create the prediction model. In this paper, we have successfully detected PD with 91.5%, 88.5% and 89.5% accuracy utilizing different CNN deep learning architectures which was trained and tested with a huge number of images. By comparing the results we can say that among these three models VGG19 works best on our dataset. To predict different stages of PD for different age or gender groups this approach can also be generalized. Moreover, researchers can perform feature selection and classification with a unique architecture with this deep learning-based solution. The application of this model becomes very easier in real-world situations by using image processing and neural network independently, i.e., this technique takes exceptionally less processing power and its accuracy is reliable. Area analysis and the use of a simple neural network is beneficial in developing prediction models by this proposed model. And this helps a physician to reduce the long procedure of diagnosis and annihilate any human error.

6.1 Future Work

Our proposed model looked at the problem of detecting PD from a distinctive angle than the existing approaches, and the results that we achieved is very much relevant to real-life situations. These results are not the means to an end, rather many works lay in advance to build up this model to be implemented in a real-life situation. Also, evaluating this model with other existing approaches on the premises of accuracy, efficiency and applicability on real-life situations can better reveal the position of this approach. By creating a usable computer software with this approach can promptly help doctors to detect Parkinson's with better accuracy than ever before. More works can be accomplished and more reliable accuracy can be achieved on datasets with a wider variety of subjects, and additionally including extra factors that come to play in regards to the disease. The accuracy achieved in this work was very high which confirms the network architecture was effectively selected. However,

more complex network architecture along with more convolutional neural layers is recommended for future works and more complex problems. Last however no longer the least, we are also very grateful to our parents, friends, and well-wishers who have supported us at some point of our research. We would also want to acknowledge the help that we received from several resources over the Internet particularly from related researches.

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