A Federated Learning Approach for Detecting Parkinson's Disease through Privacy Preserving by Blockchain

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Declaration

It is hereby declared that

1. The thesis submitted is my/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.

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Ethics Statement

We have assured complete transparency of our evaluation process in addition to providing visual interpretation of the output generated by the model.

Abstract

Parkinson's disease is a degenerative ailment caused by the loss of nerve cells in the brain region known as the Substantia Nigra, which governs movement. These nerve cells die or deteriorate, rendering them unable to produce an essential neurotransmitter called dopamine. The loss of dopamine in the basal ganglia precludes normal function when the substantia nigra neurons are harmed in large numbers. This results in the motor symptoms of Parkinson's disease, including tremor, rigidity, decreased balance, and lack of spontaneous movement. For the detection of PD, traditional machine learning algorithms have been used in many research papers. However, traditional ML algorithms always put a risk on the sensitivity of patients' data privacy. This research proposes a novel approach to detect PD by preserving privacy and security through Blockchain-based Federated Learning. FL may train a single algorithm across numerous decentralized local servers as an improved version of the ML approach instead of trading gradient information. Blockchain can be effectively used to preserve privacy and secure transactions (i.e., gradient) between local and central servers. The proposed model has been tested and evaluated by using three CNN models (VGG19, VGG16 & InceptionV3) in this research, and within these models VGG19 has the best accuracy of 97%. The result demonstrates that this model is very accurate for detecting PD by preserving one's privacy and security through Blockchain-based Federated Learning.

Keywords: Parkinson's disease, Federated Learning, Healthcare, Blockchain, Privacy Preserving.

Dedication

A heartfelt gratitude to our parents and loved ones for all the support and motivation they gave us throughout our lives. Without their help, we could have not reach this point and finish our research. May Allah bless them.

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Nomenclature

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

η	Eta
ψ	Psi
$\sum$	Single-Photon Emission Computed Tomography
ξ	Xi
$ADMM$	Alternating Direction Method of Multipliers
AI	Artificial Intelligence
BFL	Blockchain-Enabled Federated learning
CN	Capsule Network
CNN	Convolutional neural network
E	Epsilon
FL	Federated Learning
$FMRI$	Functional Magnetic Resonance Imaging
IIL	Incremental Institutional Learning
ML	Machine Learning
$MLMO$	Machine Learning Model Owner
NN	Neural Network
PD	Parkinson's Disease
$SPECT$	Single-Photon Emission Computed Tomography
SVM	Support Vector Machine

Chapter 1

Introduction

1.1 Overview

Parkinson's disease affects the nerve system that progresses over a long period, resulting in the degradation of the body's motor system and even the brain's capabilities. This illness starts typically primarily with minor symptoms and gradually worsens. Parkinson's disease symptoms vary from patient to patient. However, the most common symptoms are tremor, slowness of movement (bradykinesia), rigid muscles/stiff limbs, loss of automatic movements, stooped posture. There is currently no specified cure for the illness. However, detecting every symptom from an early stage and developing a suitable treatment for individual patients can reduce the symptoms of the disease.

Therefore, detecting the disease at the early stage & classifying the symptoms of individual patients is crucial for battling against this disease. Parkinson's disease's early symptoms get overlooked, resulting in patients not seeking medical attention. We propose an Ai-based detection system that can detect and classify the disease early to overcome this obstacle. All while keeping the patient data secure & private.

Federated learning emerged as a clear and practical answer to the challenge. We can detect Parkinson's disease symptoms utilizing data from a patient's mobile device using Federated learning, without the data ever leaving the system. Thus, the patient's information is kept confidential. When it comes to the medical sector, the privacy of the data is as crucial as any other primary sector.

Every year a large amount of medical data comes under attack by hackers all over the world. Among these, 77.65% of data breaches happened in healthcare provider organizations in 2019 [1]. Also, according to [1], medical data breaches in 2019 have increased 37.47% compared to last year. This number keeps growing year after year. The article also states that in 2019 alone, 59.41% of this data breach is due to hacking/IT incidents. Every year the healthcare industry produces a lot of sensitive data like patient records, insurance information, credit card information, research data, transnational documents. Through cyber-attack, this data gets taken by hackers and then either gets sold on the dark web or used for ransom money from victims. It happens because of an outdated and insecure network system that is used by the industry.

Moreover, these data can also get lost or damaged if an organization's server malfunctions. Even if a medical organization's data gets lost, they cannot halt their operations, unlike any other organization. To make this data well secure and not hackable, using decentralized blockchains comes as the most viable method. This paper uses the Federated Learning and Blockchain for detecting Parkinson's Disease by preserving one's data privacy and security.

1.2 Problem Statement

Patients with Parkinson's Disease (PD) have a wide range of motor and non-motor symptoms, as well as cognitive decline [2]. This serious condition has a cumulative negative effect on the patient over time [3]. People with history of Parkinson's disease in their bloodline surely to get the condition themselves, which affects 7 to 10 million people worldwide [4]. PD is used to examine around 60,000 people per yearly US [3].

For detecting Parkinson's disease, [4] used three different CNN architectures to extract the features from FMRI images where the data had been compared to get better accuracy in detecting PD, and 91.5 percent is the highest level of accuracy obtained. The way important information in PD biomarkers is retrieved and processed has undergone a paradigm shift due to ML. The use of machine learning algorithms, which provide relevant information, can also expedite the diagnosis of Parkinson's disease. According to [5], Four classifiers were investigated in diagnosing PD: Decision Trees, Regression, DMneural, and Neural Networks (NN). The NN technique had the most fantastic accuracy of 92.9 percent. Healthy persons can be distinguished from those who have Parkinson's disease (PD) by measuring their dysphonia [6]; Due to the support vector machine's (SVM) capacity to extract nonlinearity via nonlinear kernels, for the categorization of PD, it is only used to classify four distinct dysphonic characteristics.

Therefore, traditional machine learning algorithms are perpetually exposed to data security and privacy concerns. Data privacy and security necessitates maintaining data confidentiality, as privacy cannot be guaranteed if data are vulnerable to unwanted access. Existing solutions for machine learning algorithms cannot afford to be secure.

Traditional machine learning algorithms are run in a centralized data center, and data owners upload their data there; as a result, data is private, and owners are hesitant to share, [7]. Additionally, data collection is a time-consuming and challenging task which is crucial for machine learning improvement. ML is becoming a commodity service that individuals use regularly. If machine learning algorithms provided by unfaithful parties are applied blindly, the sensitive information included in the training set will be exposed [8].

For instance, Understanding an illness, individual patients medical records were consulted; the condition can be diagnosed using a model that is similar to that of the patient [9]. However, a centralized data center in ML often consumes many risks about data privacy as attackers can access the data that clients upload. Also [10], says that an attacker can reconstruct sensitive data from the client's device by executing the collaborative learning algorithm. Additionally, the attacker can affect the learning process and retrieve data from the client's gradients. The objectives and tactics of attackers have widened as machine learning trains the model connecting through a central server which attackers find easy to breach and exploit the data.

To solve the aforementioned issue, we propose a Federated Learning model based on Blockchain technology. Federated Learning has proven to be a promising paradigm

for maintaining the privacy and security of clients' data. Federated Learning is a fundamental idea that enables the development of machine learning models using data sets spread across multiple devices while preventing data leakage. FL enables several participants cooperation on instruction to a machine learning model without exchanging local data. Protection of data is one of the necessary attributes of federated learning.
Using federated learning (FL), Decentralized data analysis eliminates the requirement to submit data to a central server; Thus, the data retains its utility despite being stored locally [7]; In this federated way, The confidentiality and privacy of source data are meant to be maintained. However, according to [11], the federated approach to model training is prone to model poisoning assaults. For the issue above, we adapted Blockchain in our federated learning model.
The blockchain is a decentralized public ledger that stores a record of every transaction that has ever taken place on the network, and an entire block is made up of a header and body [12]. The previous block's hash appears in the header of each new block, and each block structure is built on top of the one before it, forming a chain or linked list [12].
In our proposed model, there will be four client servers, where clients will compute training gradients in each of their servers through distributed learning algorithms. In [13], demonstrated that gradient updates can leak a large amount of information about clients' training data. So, to avoid this issue after training, each local server will send gradients to the central server, and in this way, for every communication round, there will be transactions, and for every transaction, one block will be added, and it will create chains with upcoming transactions. Likewise, the central server will train those gradients through the Fed Average algorithm, and updated gradients will be sent back to the local servers. Based on Blockchain technology we make a plan to build a federated learning paradigm. We will utilize the proof of concept for validating the transactions (i.e., gradient) through Blockchain.

Therefore, the questions this research trying to answer is:

How effectively can we detect Parkinson's disease by preserving one's privacy and security through Blockchain-based federated learning?

Lu et al. [14]; proposed data sharing to be made more secure by utilizing Blockchain, FL, and differentiated privacy; though they did not use gradients, differential privacy noise may significantly impact accuracy.
Lyu et al. [15]; made the first attempt at federated fairness in a decentralized deep learning environment aided by Blockchain, which was a success, and the authors developed a technique for enforcing fairness through reciprocal evaluation of local credibility. Additionally, they developed a three-layered onion style encryption approach to secure the correctness and confidentiality of their data.

This research will respond to the aforementioned question by training and investigating Parkinson's dataset through a Blockchain-based Federated Learning model.

1.3 Research Objectives

The research aims to build a Blockchain-based Federated Learning model were preserving the privacy of PD, which can be detected from a dataset where the dataset can be distributed and train those distributed datasets in a decentralized way, in four separate client servers. Furthermore, after training the datasets locally, the gradients will be sent by all the client servers to a central server from where the updated gradients will be again sent to the local servers like that communication round will be going on as local servers will be sending limited epoch continuously to the central server. Here Blockchain comes into play for the decentralization of the learning process of our system.

1.3.1 Securing data by merging Blockchain and Federated Learning

Combining the Blockchain and Federated Learning protocol would allow clients to check upon previous rounds or each latest block that is currently going on and go to the next round of the data aggregation. It will bring us towards fulfilling one of our most crucial research objectives, i.e., avoiding a malicious central server for incorrect data accumulations and decentralization. In this case, if there is a central server in place of 4 different client servers, a server failure would have stopped the entire training, but that is not the case when it comes to our decentralized servers. The main aims of this research are,

1. To get a thorough understanding of FL and its functions.
2. To extensively explore Blockchain and how it works on privacy-preserving.
3. Designing a Secured Parkinson's Disease Detection System by using a variety of acceptable characteristics to classify.
4. To significantly improve the privacy of sensitive clinical data shared by the clients.
5. To test train datasets in separate devices remotely for increased efficiency and reduced time consumption.
6. To evaluate the model.
7. To provide feedback on how to make future work's frameworks better.

Chapter 2

Literature Review

For getting statistics and research data for improving the system while ensuring complete user privacy and relevant results, federated learning is the best viable solution. Where any deep learning models fail to improve due to lack of data, combined learning excels by collecting locally trained models rather than the data itself. This way, any type of medical data would never have to leave the user's device, keeping private data private. Adding blockchain to the equation makes privacy & data security complete. This Blockchain-Enabled Federated learning is also known as BFL. The worldwide implementation of FL may guarantee excellent clinical decision quality independent of the treatment site. With comprehensive traceability of data access, hospitals and clinics can minimize the danger of third parties misusing their patient data. An FL framework will be developed and implemented at four French hospitals [16]. We think it has great potential to improve medical care by enabling more precise diagnosis.

2.1 Federated Learning

Federated learning uses mobile devices to train a Neural Network (NN) model, then sent back to a (MLMO) aslo known as Machine Learning Model Owner. In this case for example, a server. The server aggregates these models and sends them back as a global model. This process repeats itself until the global NN model achieves a sure accuracy. In FL, any transaction & model data is kept in the MLMO server. If the MLMO server gets damaged or malfunctions, the records, and the model kept there will get lost or damaged. The model must be retrained if this occurs. To counter this problem, we use blockchain with FL.

2.2 Blockchain

Nowadays, Blockchain is commonly used for all sorts of immutable transaction records. It uses a shared, decentralized way to keep the records in separate identical databases. This way, the data can protect it from any damage, which addresses the MLMO's lacking. This database is shared among the public, any group or organization. Once a transaction gets saved to the shared ledger, tampering or editing is quite impossible for participants or miners. If an anomaly is found in a transaction record, a new transaction must be made to correct the problem while both transactions are visible [17]. In recent times, Blockchain has been recommended as a better approach in FL. In [18], it is said that Blockchain can store transaction data and secure the privacy of mobile devices in FL. Also, it can be utilized to prevent any harmful mobile devices in FL, as shown in [19]. Blockchain ensures the security of the data by verifying the transaction record by many devices before making any change.

2.3 Related Works

Although federated learning is a relatively new concept, it has already been implemented & researched by many researchers. In [20], the security of FL is somewhat lackluster as the model and the central server can be affected by malicious devices. Federated learning consists of two roles, and one is participating mobile devices and the central server. In this framework, user privacy may be protected. However, the system is still not immune to cyber attack. In FL, the central server is in charge of training the model. The server sends an initial model to every participant device. After this, the participant device starts to change the model according to the data at hand. Then the updated model gets back to the server forming a new global model. This new model gets sent back to the selected participant devices. This cycle continues until the desired result is achieved. In [20], the central server is replaced by a blockchain that contains the global and local model changes. This way, they can prevent any corruption or cyber attack on the model. They also implemented Committee Consensus Mechanism (CCM), which determines the correct data block to be added to the chain. CCM may be fast at determining preferred data from appropriate devices, but it lacks the desired accuracy.

When training a new ML model, a system is constantly faced with vast amounts of data. In [21], a normalization process is introduced to organize the massive amount of data generated in the medical industry. Then they use a Capsule Network (CN) to get better results than other known models. However, the algorithm is relatively slow due to its dynamic routing's inner loop.
In [22], an end to end framework is proposed for data standardization. Moreover, to avoid any bottleneck in training the model, they used the Alternating Direction Method of Multipliers (ADMM), which requires fewer iterations. Although this framework has high potential, it still needs in-depth research and be applied to large amounts of data to confirm its accuracy. When most of these papers propose not using centralized servers for FL model training, [23] proposed a unique system that uses a central server to control the model training as public network devices are not often available for training any local models. Their proposal is viable to a certain degree. However, it comes at the risk of losing the whole model.

According to [24], increasing access to data via multi-institutional private data partnership, may improve a model quality better than the collaborative approach. The impact of data distribution among cooperating institutions on model quality and learning patterns federal learning (FL) had an advantage over other collaborative methods such as incremental institutional learning (IIL) and cyclic incremental learning (CIIL), which were compared with FL. It was discovered how well FL performed than IIL and CIIL. FL improves models at the fastest pace among the

data-private collaborative learning approaches.
The research work [24] showed how collaborative data and FL approaches could achieve complete data learning while ignoring the need to share patient information and support broad multi-institutional collaboration to overcome technology and data ownership issues and support data protection regulatory requirements.

According to [25], early detection is critical to slow down Parkinson's disease (PD) intensity. The number of persons affected with PD globally has reached more than 10 million. Early PD diagnosis is a critical aspect in stopping its progress at an earlier stage. Numerous methods have been developed to aid in detecting PDs using various measurements, including speech data and gait patterns. In academic and commercial research on Parkinson's disease (PD) diagnosis, machine learning (ML) has emerged as a potential subject. In addition, machine learning methods give relevant information that assists PD categorization and diagnosis to accelerate decision-making. There were three standard machine learning methods for Parkinson's disease based on acoustic speech analysis: random forest (RF) or vector support (SVM) and neural network. The research developed a deep learning model using premotor characteristics to distinguish between PD affected and healthy. The suggested deep learning model had a high detection accuracy of 96.45%, which was impressive. The early identification of PD is crucial for a better understanding of the origins of the illness for therapeutic procedures and therapies.

According to [26], to diagnose PD, the presence of four cardinal motor symptoms like postural instability, resting tremor, stiffness, bradykinesia is required. These symptoms occur only after a 60% decrease in dopaminergic neurons. Thus, early diagnosis of PD is critical for early treatment and administration of neuroprotective therapies when available. According to some research, individuals may be classified as having early stage PD. The University of Pennsylvania Smell Identification Test, also known as UPSIT and the Sniffin'Sticks test (SS) is used culturally modified translations to identify smells in 106 people with PD and 118 healthy individuals' 85.3 percent accurate results with SS test, 81.1 percent sensitive results with UPSIT, and 83.5 percent accurate results with UPSIT. From using logistic regression, the same study found that including more subjects (among 193 PD and 157 normal ones) improved classification accuracy for both the SS test and the UPSIT, with the SS test having a higher accuracy, sensitivity, and specificity (88.4 percent, 90.4%, and 85.5 percent, respectively). SPECT scan data from 79 patients with Parkinson's disease (PD) and 37 non-PD subjects were analyzed with a Naïve Bayes classifier to obtain a accuracy of 94.8%. For the most part, people use machine learning approaches like logistic regression, SVM, and ensemble algorithms to identify Parkinson's disease (PD) in speech signal data. However, the outcome was positive. However, this research had a drawback: no characteristics were combined for classification or small sample sizes.

According to [16], Artificial intelligence (AI) research has led to disruptive radiology, pathology, and genomics advances. To achieve clinical grade accuracy, modern deep learning models need massive curated data sets with millions of parameters. They also generalize effectively to new data. Assembling and maintaining an extensive collection of high quality data takes time and money. Federated learning (FL) trains algorithms without sharing data to solve data governance and privacy concerns.

Recent research shows that FL-trained models usually outperformed models that are trained on centrally hosted data sets from single institution. In medical imaging, using FL for whole brain segmentation and brain tumor segmentation is useful. Because FL is new, it is essential to highlight that agreement must define its scope, purpose, and technology. The global use of FL may provide good clinical decision quality regardless of the treatment location. Hospitals and clinics can reduce the risk of third parties abusing patient data by tracing data access.
In the research paper [5], several classification methods were implemented to effectively diagnose Parkinson's Disease, i.e., Neural Networks, DMneural, Regression and Decision trees. These schemas were compared using different assessment techniques for calculating the overall performance rating of the classifiers. The results show that the Neural Networks classifiers have the best performance with an accuracy of 92.9%. A comparison was also made with kernel SVM proving Neural Networks classifiers as more accurate here.

According to the research paper [27], for early identification of Parkinson's Disease, vocal disorders were connected to symptoms in 90% of Parkinson's Disease patients in the early stages. This necessitates the use of vocal features in computer assisted diagnosis and remote patient monitoring, resulting in increased accuracy and lowered the number of specified vocal features in identifying Parkinson's disease. The four classifiers used are multi-layer perceptron, support vector machine, k nearest neighbour and random forest, yielded 94.7 percent accuracy, 98.4 percent sensitivity, 92.68 percent specificity, and 97.22 percent precision. They are improving upon this accuracy, while it is achievable to reduce the corresponding computational complexity by feeding relevant and uncorrelated features to the classifiers. This has been done by feeding 8-20 features or, more recently, 50 features to the classifiers. So, it is evident that additional features can be improving the accuracy here for early detection of PD.
The Patient Questionnaire (PQ) section of the Movement Disorder Society-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) is utilized to construct a prediction model to diagnose PD early in the research work [28]. To validate these, both subject and record-wise, increasingly popular machine learning approaches such as logistic regression, random forests, boosted trees, and support vector machine (SVM) are being applied. These approaches achieve high accuracy and area under the ROC curve (both $> 95\%$).

A more recent paper [29] focuses on the decentralization of the learning process and incentivization of Blockchain in ML for an advanced system of privacy-preserving FL in fields of medicine. They provide a framework for this Blockchain orchestrated ML system for privacy-preserving FL and six critical elements for the approach. Data and analytic processes, for example, are discoverable on the secure public Blockchain while maintaining the data and analytic processes' anonymity. Value created by generating previously unlawful, immoral, and infeasible data/compute matches. Federated learning and improved cryptography give compute assurances. Privacy assurances and hardware cryptography are provided by the software. Insufficient data is rejected using model poisoning avoidance strategies, and data quality is rewarded with tokenized reputation-based incentives.
In addition, the research article [30], optimizes Federated Learning by establishing a new performance indicator, training efficiency, to speed up convergence and to

improve the training process efficiency. The non-convex training efficiency maximization problem was solved using an efficient technique. The research looked at how to allocate bandwidth, batch size, and user selection for federated learning at the network edge. Experiments suggest that this method improves learning performance more than traditional methods.

From the above discussion, we see that most of these existing research works on detection and diagnosis of PD shows the lack of privacy preserving and data protection and also creates hindrance in proper diagnosis. There is a research gap about how such sensitive medical data of the PD patients would stay confidential without data leakage. Very little research has been done on this aspect of the medical data of Parkinson's Disease Patients. So, there is still room for improvement here, as seen even with implementation and comparison of other classification methods. A relevant research [29] shows how utilizing Federated Learning methods incorporated with data security of Blockchain would help in increasing the accuracy along with fulfilling the lack of clinical data protection.
The learning performance of the Federated Learning model can also be enhanced by the application of an efficient algorithm for more accurate results [30]. Therefore, after reading all these research papers, we got the plan and proposition for coming up with a Federated learning approach for detecting Parkinson's Disease with the robustness of decentralized learning and ability to protect the data by privacy-preservation of Blockchain.

Chapter 3

Background Study

3.1 Parkinson's Disease

Parkinson's disease is a degenerative neurological ailment that causes a deterioration in quality of life [2]. It may be a constantly-compounding neuronal mess. This disease resembles extrapyramidal clutter with no clear philosophy. Other sorts of extrapyramidal clutter called Parkinsonism include vascular, defilement, damage, somnolence-generate, and carbon monoxide toxin. Other neurodegenerative extrapyramidal disorganizations include energetic super-atomic loss of mobility and process rot. Detecting this condition is difficult.

This sickness is a typical movement snarl. Only 4% of people with PD are tested after age 50, despite the fact that the frequency of PD rises with age [3]. Every year, more than 60,000 patients in the US gets affected by PD [3]. Globally, 7–10 million people suffer from this disease. Caucasians have it more. Pd affects males 1.5 times more than women. Herbicides and pesticides may cause Parkinson's disease. It happens when substantia nigra and basal ganglia dopaminergic neurons die [31], [32]. It produces trembling, stumbling, muscle stiffness, and slowness. Not random assignment determines PD sub-classifications, but severity. It's mild, moderate, or advanced. 80% of PD patients are idiopathic due to unclear philosophical foundations [33]. Genes linked to PD risk. Affected genes include LRRK2, PARK7, PRKN, PINK1 and SNCA.

Impedance and impairment may be measured using a variety of plates. Most often utilized are the UPDRS and HY scales [34]. An examination of illness development using a framework ranging from (no evidence of disease) to 5 (the UPDRS gives a full study of incapacity and impedance) (extreme). MDS-UPDRS is a rebuilt and improved variant of the original UPDRS, including current modifications to non-motor components of PD to make it more complete [35]. Previously notable distinctions were consuming scotch guidelines and definitions and a concentration on lesser side effects and symbols.
PD genetic variations abound. Recent data suggests that genetic chance variations also affect the disease's medicinal benefits [36]. Although genetic variables undoubtedly influence PD sub-type determination. Annual changes in Parkinson's disease symptoms can be predicted by moving the Movement Disorder Society-Unified to include genetic information Parkinson's Disease Rating Scale [37]. A trembling paralysis essay by British chemist James Parkinson was published in 1817 [38].

Parkinson's explanations, others had before defined the ailments that would carry his name, but the 20th century improved information about diseases and treatments. PD was once called the inability to move or shaking paralysis. "Parkinson's disease" was coined in 1865 by William Sanders and popularized by Jean-Martin Charcot a French neurologist, Parkinson's disease may be a congested, worried energetic framework that inhibits development [39].

Early literature mention Parkinson's-like symptoms. An Egyptian papyrus from the Twelve century B.C. portrays an aging ruler dribbling, while the Bible mentions microseism [40]. It's not clear if the tremors, developmental delay, dribbling, and other symptoms in the Ayurvedic restorative book are from PD or not. This disease was worse by treatments found in mucuna, which is high in L-DOPA. Galen depicted PD-like tremors, postural changes, and loss of mobility. Later in Galen's life, there are no well-known bibliographies devoted exclusively to this disease until the sixteenth century [40]. John Seeker's meticulous representation of the sickness may have inspired Parkinson to assemble and exhibit persons suffering from "loss of mobility paralysis." Finally, Auguste Francois Chomel included a few depictions of abnormal growth and inflexibility in his pathology dissertation, which was contemporaneous with this work.
In Parkinson's disease, side effects begin gradually, initially with a barely fair one has a noticeable tingle. Although Frissons are well-known, the congestion frequently functions as a source of strength or a barrier to growth. During the early phases of Parkinson's disease, resistance may manifest as minimal or no aspect.
By the late 1980s, regional cerebral blood flow increased zones of dense neuronal activity activation, as shown by PET with low resolution studies in humans [41]. Parkinson's disease has no known cure at this time, however drugs and surgery can help lessen the illness's symptoms.

However, detecting every symptom from an early stage and developing a suitable treatment for individual patients can reduce the symptoms of the disease. Therefore, detecting the disease at the early stage & classifying the symptoms of individual patients is crucial for battling against this disease. Parkinson's disease's early symptoms get overlooked, resulting in patients not seeking medical attention. This early symptom can be detected using SPECT which is emission computed tomography with single photon, the transporter for dopamine imaging shows how much dopamine is being transported across the brain. We propose an Ai-based detection system that can detect and classify the disease early to overcome this obstacle. All while keeping the patient data secure & private.
Federated learning emerged as a clear and practical answer to the challenge. As a neuro imaging technology, the following are some of the most important aspects of FMRI: The hollow tube of an MRI scanner contains a powerful magnetic. Nearly 50,000 times the World's field strength, the scanner's field strength is three teslas (T) [4]. The magnet impacts iota cores. An attractive region rearranged the cores to fit the area's direction. Larger areas are better organized. When pointing in the same direction, each core's magnetic signals create a large flag. fMRI finds the hydrogen flag in water (H2O). The approach's high affectability may cause it to cover. Relaxing state, it is a non-invasive neuroimaging biomarker for neurodegenerative illnesses like Parkinson's. We are encouraged by the excellent accuracy and affectability of the stream model based, data-driven separation of illness sufferers

from healthy controls via the full-brain between-network network. This project will use fMRI data with federated learning and blockchain to identify early Parkinson's disease. Science and technology have machine-controlled everything. To construct our study, we will employ a variety of ML and DL settings.
Parkinson's disease is characterized by dynamic muscular ascendancy catastrophe, solidity, gradualness, and inability to adapt. Gradually losing reason may make passing, conversing, and completing basic assignments difficult. Individuals' development and impedance differ. Others with Parkinson's disease become crippled considerably faster than others. Parkinson's complications include trauma-related falls and pneumonia. According to research, people with Parkinson's disease had a survival rate that was on par with that of the general population.

3.1.1 Broad Description

Numerous research projects are being conducted on PD, making it the second most prevalent disease globally and is growing at an alarming rate each day. This condition necessitates the development of a framework for PD decision support. Today's computational gadgets have been defined to assist professionals in making decisions about their patients. Artificial Insights treatments are a necessary component of physical clinic visits for observation, and medications are inconvenient. Increased Web connectivity and media transfer speed enable unreachable patient care, however increasing significant opportunities for reducing the bother and expense of personal visits. However, there is a requirement for dependable clinical observation devices to exploit these gaps.
While the disorder is defined by tremors and difficulty walking, most patients experience communication difficulties, most notably slurring and what is recognized in the field as feeble voice. At the same time, 89 per cent of people with PD are involved in various types of discourse difficulties. If the Parkinson's infection classification rate is high, slightly earlier Parkinson's may be predicted. Usually, the conclusion is based on a framework for healing and a neurological framework examination utilizing the Linked Parkinson's Disease Rating Scale (UPDRS). It is that PD is notoriously difficult to foretell in the early stages of the disease. To increase diagnostic accuracy and help professionals make better decisions, AI-based programming approaches are necessary.

3.1.2 Goals

Parkinson's Disease (PD) is a chronic disorder that causes tremors, cognitive failure, dissociation from reality, dementia and sleep difficulties. Around ten million people worldwide have Parkinson's Disease [42]. Each year, approximately 1600 people in Bangladesh succumb to Parkinson's Disease. PD is incurable [42]. A shift in dopaminergic neurons can be observed around ten years after the first occurrence of tremor or engine symptoms. Parkinson's disease (in its early stages) is characterized by a reduced sense of smell, disorder during sleeping with a lot of fast eye movement, small handwriting, and difficulties moving around one's body. Preventative measures, such as avoiding unneeded therapeutic tests, treatments, and expenditures as well as security hazards might lead to the early discovery of Parkinson's disease (PD).

Until recently, doctors decoded these images in several hospitals, with the possibility of human error involved. The pooled accuracy of this condition's medical diagnosis is 80.6 per cent [42], we devised a novel and uncomplicated procedure for distinguishing Parkinson's Disease at the initial stage by utilizing Federated Learning and SPECT scans. By incorporating this innovation into healing facilities or demonstration facilities, enhance the accuracy of Parkinson's disease diagnosis and reduce costs while also increasing efficiency.
For detecting Parkinson's disease, [4] used three different CNN architectures to extract the features from FMRI images where the data had been compared to get better accuracy in detecting PD, and 91.5 percent is the highest level of accuracy obtained.
Due to ML, the way PD biomarkers is retrieved and processed has undergone a paradigm shift. And Implementation of Federated Learning will speed up the detection process manifold.

3.1.3 Different Parkinsonism Syndromes

Essential Tremor

The wrists and forearms tremble in a constant, bilateral fashion in those with essential tremor. Due to bradykinesia, stiffness, and postural instability, about 20% of people with critical tremors are misdiagnosed with PD or the other way around. Essential tremor occurs immediately upon arm extension, but Parkinson's disease causes a delayed re-emergence of tremor with arm extension. A rest tremor (10%) or a unilateral motion (5% of cases) might aggravate an otherwise normal essential tremor. Head, voice, and alcohol sensitive tremors are essential tremors. Essential tremor is commonly inherited as an autosomal dominant characteristic; a genealogy of the same tremor may consequently be a good indicator. Unilateral rest tremors, leg tremors, stiffness, and levodopa sensitivity reflect Parkinson's disease. A dopaminergic deficit is shown by PET imaging in patients who have resting and postural tremors without bradykinesia or stiffness. Monosymptomatic Parkinson's disease is diagnosed after two years of resting tremors.

Vascular Parkinsonism

VP describes Parkinsonism in cerebrovascular disease patients. It is difficult to diagnose the ailment without ruling out Parkinsonism variants. A research of eleven people with basal ganglionic capsular infarcts found just 1 occurrence of inverse Parkinson's disease. Infarcts in the basal ganglia affecting the putamen, putamino-pallido-thalamic connections, or substantia nigra may cause early onset contralateral Parkinsonism. MRI scans and clinicopathological tests show that vascular lesions in vascular Parkinsonism are mostly in these 2 areas. Multiple lacunar infarcts block the flow of information from the thalamus to the cortex. This can lead to progressive Parkinsonism that only responds to levodopa fifty percent of the time.

Progressive Supranuclear Palsy

Progressive supranuclear palsy, also called Steel-Richardson-Olszewski syndrome, can be easily distinguished from Parkinson's disease by the patient's mostly Patients with Parkinsonism and pseudobulbar palsy are also likely to have an abnormally high degree of frontal lobe syndrome, as is the case here. This illness could be mistaken for Parkinson's disease in its early stages, before abnormalities in the way a person looks, in people who don't have when full-blown PD's main symptom. Studies show how often Parkinson's is misdiagnosed. Progressive supranuclear palsy causes without a tremor while sleep in the both the cervix and the torso. Bradykinesia is a severe symmetrical disorder. During the early stages of the condition, patients experience postural instability and slips and trips. Strides are broad and unsteady in contrast to PD. Vertical supranuclear palsy and unsteadiness after a fall must emerge throughout the first year of illness to be considered progressive. A retrospective study found these criteria had greater precision, empathy, and positivity of predictive value than others. Progressive supranuclear palsy is sporadic but can be familial. Severe Parkinsonism may benefit from levodopa. Progressive supranuclear palsy's movement and coordination problems are caused by death of the cell in the brain sectors.

Multisystem Atrophy

Synuclein oligodendrocytic inclusions are related with multisystem atrophy. Autonomic dysfunction may be seen in cerebellar sector. MSA-p, the It's difficult to tell the difference between Parkinsonism and Parkinson's disease in the multisystem atrophy caused by Parkinson's. MSA-p is harmful. Although it affects a shorter age range than Parkinson's, it peaks in the sixth decade. Only a major disease may be diagnosed accurately. Early autonomic dysfunction appears as impotence or postural hypotension, or a unique cerebellar condition. The following clinical manifestations can assist in distinguishing between MSA-p and Parkinson's disease: Symptoms of the pyramidal tract, severe dysarthria, and inadequate or temporary dysarthria reaction to L-dopa Levodopa may initially help MSA-p Parkinsonism, although dyskinesia and motor fluctuations may follow. However, dyskinesia usually affects the orofacial and cervical musculature.

Corticobasal Degeneration

Corticobasal degeneration is an extremely uncommon form of tauopathy that has impersonal and genetic characteristics with PSP. Clinical symptoms include unilateral Parkinsonism, frontal lobe degeneration, multiple sclerosis, Alzheimer's disease, and growing apraxia. Most people with Corticobasal degeneration arrive in their sixties with a unilateral jerky tremulous akinetic inflexible extremities. Although it is rather uncommon, difficulty to perform accurate finger motions can be challenging to differentiate from bradykinesia, stiffness, and dystonia. 50% of individuals have alien limb syndrome and cerebral sensory abnormalities. While parkinsonian rest tremor is a typical symptom, it is not frequent. At presentation, the majority of patients do not exhibit signs of worldwide cognitive impairment or dysphasia; nevertheless, dementia often emerges late in the disease's course and may be the presenting symptom in some persons. There is a poor response to levodopa for motor symptoms, and the disease advances quickly, becoming significant impairment on both sides in two to seven years. Supranuclear ophthalmoplegia is not the same thing. This is unusual in advanced illness..

Other Parkinsonism Syndromes

Other Parkinsonism symptoms might insurmountable to identify from Parkinson's. The most prevalent kind is medicine-induced Parkinsonism. To counteract the effects of dopamine, especially antipsychotics and antiemetics, can cause Parkinsonism. Medicine-induced Parkinsonism can resemble PD symptoms, including rest tremor. Drug-induced Parkinsonism is difficult to diagnose. Unknown drug history, small dosages of antidopaminergic medications, and non-regression of Parkinsonism after withdrawal of offending drugs pose unique challenges, signaling that It's possible that the medicine-induced condition is caused by PD. In situations of Parkinsonism, neuroimaging may be helpful for detection of the symptoms. It is also possible, for instance, for psychical Parkinsonism or drug-induced Parkinsonism to coincide alongside Parkinson's disease [43].

3.1.4 Clinical Features of Parkinson's Disease

TRAP stands for Resting Tremor, Rigidity, Akinesia, and Postural Instability. Bent posture and freezing in People with PD are the most common kind of Parkinsonism. Given the large diversity of PD patient features and behaviors, motor and nonmotor impairments are relevant. Most rating methods used to assess Parkinson's motor impairment and disability are inaccurate and unreliable. The Hoehn and Yahr scale ranges from zero (no illness) to 5 (progressive illness). The UPDS is the most widely used scale for evaluating disability (UPDRS). When it comes to Parkinson's disease (PD), the pace of deterioration varies depending on where you are in the illness's progression and gait issues (PIGD). Our study indicated that in 297 patients with clinically confirmed PD, UPDRS scores dropped 1.34 points to 1.58 points yearly periodically (181 males, 116 women). These patients advanced quicker than tremor dominant Parkinson's patients. Only handwriting did not decline in UPDRS. Multiple studies show younger people are more prone to levodopa-induced dyskinesias. In a four-year, 145 clinic-based patients studied and 124 community-based patients, scores on motor skills and dysfunction declined by 2.4-7.4% yearly. Improvements are being made to the present UPDRS to increase its sensitivity to small changes and to add motor less components of PD into the analysis. In addition to assessing mental symptoms (such as depression), other rating measures are employed to evaluate overall quality of life [44].

Bradykinesia

Bradykinesia is a Parkinson's symptom which includes Depression. Bradykinesia is the inability to plan, start, and execute sequential and concurrent activities. Early signs include slow daily tasks, mobility, and response times. Fine motor skills may suffer (eg, buttoning, using utensils). Bradykinesia can induce a lack of spontaneous movements and gesticulation, drooling, monotonous and hypophonic dysarthria, hypomimia, reduced blinking, and decreased arm swing when walking. Bradykinesia is an speedy sign of PD. In bradykinesia, hands and feet pronate or supinate. Bradykinesia is a mood-dependent parkinsonian symptom. An immobile person can grab a ball. Parkinson's patients retain intact motor programs but struggle to access them without an external stimulation like a visual or musical cue to overcome a hurdle. Dopamine deficiency causes bradykinesia. Decreasing number of neurons in senior parkinsonians' substantia nigra verifies this. The striatum and accumbens-caudate complex absorption of 18F-fluorodopa is decreased in PD. Reduced dopaminergic function in the motor cortex causes bradykinesia. Cortical and subcortical circuits that control movement kinematics are less active (eg, velocity). Several premotor regions are activated, including visuomotor control. Putamen and globus pallidus look inadequate, leading in muscle weakness.

Tremor

Rest tremor seldom affects the neck/head or voice. Essential tremor, cervical dystonia, or both cause head tremors. Supination–pronation tremors (pill-rolling). Exercise and sleep stop rest tremor. Some people have "internal" shaking. Postural tremor can develop years or decades before parkinsonian tremor. According to study, essential tremor increases Parkinson's risk. Tilt is a common sign of postural tremor. Parkinson's postural tremor is horizontal. Re-emergent tremors are treated with dopaminergic medication, making them a subtype of rest tremor. Essential tremor symptoms include movement tremor, head and vocal tremor, and absence of horizontal arm latency. Parkinson's disease tremors, tremulous handwriting and spirals, and alleviation with alcohol or beta-blockers. It depends on the patient's condition. Patients with Parkinson's exhibited 69% rest tremor at diagnosis and 75% throughout their disease, according to Hughes et al. 9% of late-stage patients had no tremor. A prospective investigation found tremor in autopsy-proven disease patients. . Patients with PD suffering from tremor, neurons degenerates in midbrain (A8) in a subgroup.

Rigidity

Resistance increases with rigidity, occasionally associated by "cogwheel" occurrences, and occurs across the passive range of limb motion. The Froment's movement exacerbates stiffness and is useful for identifying moderate instances of rigidity. Shoulder discomfort is one of the most commonly misunderstood early signs of PD, misinterpreted as rotator cuff injury, arthritis, or bursitis. A research of six thousand thirty-eight people (average age 67-69 years) found that Unsteadiness, tremors, and an overall lack of balance increase Parkinson's disease risk (threat ratio's 2.12, 2.10 and 3.49, respectively). This population had 56 more PD cases after 5.8 years of follow-up.

Postural Deformities

Axial stiffness can lead to abnormal neck and trunk postures (e.g., anterocollis, scoliosis). Rigidity often causes flexed neck, trunk, elbows, and knees. Late in the disease's course, flexed posture develops. Some individuals may develop striatal limb anomalies (striatal hand, striatal toe). Striatal hands have ulnar deviation, metacarpophalangeal flexion and proximal, distal interphalangeal extension and flexion, striatal feet have toe extension or flexion. In one study, 21% of individuals with Parkinson's disease had striatal toe (big toe extension). Patients with striatal abnormalities are younger and develop parkinsonism faster. Excessive neck flexion, truncal flexion (camptocormia), and scoliosis are skeletal diseases. Camptocormia causes thoracolumbar flexion. Walking aggravates the condition, while sitting, lying supine, or voluntarily extending the trunk while leaning against a wall, elevated walker, or table alleviates it. Dystonia or extensor truncal myopathy can also produce camptocormia. The Pisa syndrome is a truncal malformation that causes the trunk to lean forward either sitting or standing.

Postural Instability

Loss of postural reflexes causes late-stage PD postural instability. The pull test measures retropulsion or propulsion by rapidly tugging the patient's shoulders. Postural abnormality is more than two steps back or absent. Instability causes falls and hip fractures. Parkinson's can produce postural instability in numerous ways. Orthostatic hypotension, sensory age changes, and visual, vestibular, and proprioceptive input are treated as well (kinesthesia). Parkinson's sufferers' fear of falling may affect balance. 13% of respondents surveyed fell more than once a week. Sickness intensity was linked to falling. Dopaminergic treatment, pallidotomy, and DBS can relieve axial symptoms, but not postural instability.

Freezing

Parkinson's disease causes motor blockages, or freezing. But not usually all time. According to a poll of 6620 German Parkinson Association members, it's more prevalent in men and less common in those with tremor as their main symptom. Walking can cause leg, arm, and ocular freezing. It induces a 10-second immobility. Freezing affects patients' social and therapeutic life. Subtypes of freezing include start, turn, restricted, destination, and vast space hesitatation. Levodopa lowers OFF episodes. Patients become used to coldness. Rhythmic marching and changing bodily weight are examples. Freezing results from stiffness, bradykinesia, postural instability, and disease duration. Early tremor decreases freezing danger. Because freezing is frequently a late symptom or not the primary symptom, other illnesses should be considered. Dopaminergic drugs seldom produce freezing, however selegiline does. Botulinum toxin injections have not consistently helped alleviate freezing.

Sleep Disorder

Some clinicians consider sleep abnormalities (e.g., excessive weariness, sleep attacks) a hallmark of PD. Paradoxical sleep disorder, which estimated one-third of individuals with SBD engage in vigorous, potentially dangerous motor activity that includes their bed partner. Insomnia, especially interrupted sleep, is common (50%) but varies widely. Parkinson's patients lose 50% of their hypocretin neurons, causing sleep disorders. A typical symptom of exhaustion is excessive daytime drowsiness, which can also be a contributing factor. These include olfactory dysfunc tion, aches, paresthesia, akathisia, tooth and vaginal pain. Olfactory impairment (hyposmia) was related to a 10% increased risk of PD two years later compared to asymptomatic relatives. One of 62 discordant twin couples studied had impaired smell sense. Olfactory impairment is connected to amygdala or olfactory bulb dopaminergic neuron loss.

Additional Motor Anomalies

Parkinson's secondary motor symptoms might affect home, work, and driving. Facet inhibition mechanisms fail in certain persons. According to one study, 80% of Parkinson's patients had the fundamental glabellar reflex. 83.3% sensitive but not specified (47.5 percent). The palmomental reflex is more common in Parkinson's patients (34.1 percent). The glabellar reflex was more sensitive (33.3%) but less specific (90 percent). These basic reactions can't differentiate the three most common parkinsonian illnesses (PD, PSP, and MSA). Corticobasal degeneration causes several parkinsonian diseases. Opposing muscular activation causes unintentional motions. Asymmetric early Parkinson's mirror movements. Bulbar dysphonia, dysphagia, and sialorrhoea. These symptoms can be caused by orofacial–laryngeal rigidity. Parkinson's produces soft, breathy speech, pace changes, and word-finding problems. Silverman Voice Dysarthria can be treated. Dysphagia causes difficulty swallowing or laryngeal or esophageal movements. Asymptomatic early dysphagia. Swallowing issues create Parkinson's drooling. Parkinson's patients experience eye difficulties. Disease progression causes eye movement changes. Some research show no difference between Parkinson's ON and OFF phases. Ophtalmic crises and eyelid apraxia are linked to PD. Parkinson's can induce stifled breathing. Pneumonia predicts death in Parkinson's patients. Unobstructed patterns might cause arthrosis or neck stiffness. Chest stiffens from restriction. RRD affects Parkinson's patients' breathing

3.1.5 Types of Parkinsonism

Parkinsonism refers to Parkinson's symptoms and signs (PD). Gradualism, stiffness, tremor, and asymmetry (postural flimsiness). These symptoms are not exclusive to Parkinson's Disease. Hepatolenticular degeneration, multisystem atrophy, denaturation of the essential tremor, cortical basal ganglia, Huntington's disease and progressive supranuclear paralysis disease are among the conditions that are sometimes confused with Parkinson's disease [45]. This subtype responds well to medication that acts by increasing or substituting dopamine atoms in the brain [46]. Some drugs can cause parkinsonism in rare cases. Parkinson's patients may report worsening symptoms after using these medicines. Drug-induced Parkinson's disease. The drugs indicated largely suppress dopamine action, a neurotransmitter gradually reduced in Parkinson's patients' brain cells. Drug-induced parkinsonism has long-lasting consequences. Rarely, they advance with Parkinson's symptoms. Most people recover within months, and often within hours or days, after stopping the offending medicine [47].

3.1.6 The Human Brain's Basic Structure

The brain is a forty-eight-dram released within the cranium near the tactual organs [48]. An anthropomorphic head functions as a command centre for all people's bodily capacities [49]. Mainly, [50] demonstrates the distinction between conscious and unconscious intellect. The brain is responsible for various functions, including memory, sentiments, creative energy, experiences, breathing, interior temperature, and organ emanations. The human body contains five resources that provide the brain with information about the outside world. [49] These include hearing, locating, smelling, tasting, and touching. The brain regulates our cognition, communication, as well as the operation of our individual parts and organs. It also controls our pulse in uncomfortable situations. The brain stem, cerebrum, and cerebellum are the three primary brain components.

Parkinson's Disease Affects the Following Brain Regions

Brain Stem

It's called the principal second-rate head zone since it links the spine and brain. Interferes with the spinal cord's passage to the cerebrum and cerebellum. [49] The brain stem is divided into three regions: the medulla oblongata, the pons, and the midbrain. The brainstem is made up of reticular matter, which governs the body's tendon tone and regulates the brain's waking and sleep cycles. It comprises three major components: the Brain Stem, the cerebrum, and the Cerebellum.

Cerebellum

The cerebrum and brain stem are in second grade. It is wrinkled and shaped like a globe [51]. It performs the duty of controlling manipulative capacities such as posture adjustment and muscle workout arrangement. The cerebellum is responsible for synchronizing and deception motor activities such as writing, speaking and strolling.

Cerebrum

It is the brain's most prominent area, comprising both the cleared-out and correct regions of this globe [41]. There is a network of fibers called the corpus callosum that connects the two halves of this globe and carries information back and forth, also there are two halves of the globe that are accountable for each half of the body [49]. It operates this way because each side of the equator performs numerous errands autonomously. When it comes to ingenious energy, melodic capabilities, and dimensional powers, the right side of the equator is in command. Conversely, the cleansed outer reaches are in charge. Each half of the planet can be split into four distinct regions known as lobes. This region includes the frontal, parietal, occipital, and temporal lobes. One particular kind of labor is allocated to each lobe of the organ.

Lobe of the Front

The part of the brain that controls emotions, judgment, problem solving, sexual behavior, memory, and speech that is Frontal Lobe. It's our identification and communication" control panel." It's also aware of engine work, our ability to move muscles intentionally, and Broca's area. Humans have the largest, most developed frontal lobe. The anterior portion of the brain is referred to as frontal projection. The right side in frontal projection's equinoctial controls cleared-out region of the body. Frontal projection is where most brain injuries occur. Identity shifts, facial restriction, and difficulty reading one's environment can result from frontal projection damage. The frontal flap of the brain is damaged, causing engine problems and problems with conduct. The anterior projection of the brain can be large, reaching nearly halfway to the back. Stroke, traumatic brain injury, and dementia can all impair frontal projection. Frontal flaps perform different functions, so injury symptoms can vary. Abilities to comprehend or organize fewer ideas Judgment impairment. Taste or smell diminished depression motivational changes, easily distracted, sexual curiosity is decreased, enhanced, or unorthodox. Sinister or risky behavior. Frontal projection damage therapy varies by etiology. Parkinson's, Huntington's, and dementia are all degenerative disorders that are now treated symptomatically. The frontal lobe is primarily responsible for,

- Emotional characteristics
- Problem-solving abilities
- Judgment

Lobe of Parietal

The cerebral cortex, or cerebrum, is the most commonly used term when describing the brain. Average longitudinal fissure divides parietal lobe's equator sides. An evaluation of estimates, form, and spatial introduction. It is required for taste, hearing, find, skim, and scent administration. It's in the brain's major tangible zone, where it decodes input from various bodily parts. The more tactile input a bodily part gives, the larger the parietal flap should be. Because tactile information is crucial in this setting, a considerable amount of the parietal flap is dedicated to sensory input. Without contemplation, touching your nose may be a parietal lobe function. Visual talents with the occipital lobe. Count and analyze numbers. Identifying the size, form, and location of distinct jolts and things you recall. Many ideas claim that certain areas in the parietal projection are maps of visual world. Hand, arm, and eye synchronization, Linguistics, attention coordination. It is primarily responsible for the following functions,

- Reading
- Sensation
- Body orientation

Lobe Occipital

The occipital, parietal, transient, and frontal flaps of the cortex are found in each individual's brain. The global flap connects the two brain crevices and is situated right under the sidelong gap. This essential framework facilitates the handling of tangible input, such as counting torture and sound-related enhancements. It also matters how well you understand the dialect, retain visual memories, and prepare for and recall emotions. It is primarily responsible for,

- Vision

Temporal Lobe

Individual's brains include occipital, parietal, transitory, and front sector flap. The worldwide flap is located directly beneath the sidelong gap and spans both brain crevices. This essential framework facilitates the handling of tangible input, such as counting torture and sound-related enhancements. It also matters how well you understand the dialect, retain visual memories, and prepare for and recall emotions. It is primarily responsible for,

- Behavior
- Memory
- Language comprehension

3.2 Federated Learning

Federated learning was first introduced in 2016 by google to solve centralized machine learning problems. Centralized machine learning system creates verity of problems. For example,

- Large number of data needs to be at the central server for the algorithm to be learning
- Creates opportunity for hackers to hack into the central server and steal that data.
- The central server's data can also be compromised by data corruption.
- Gathering this large sum of data can cause traffic in the central server & hamper user experience.
- As these data are user's private data, due to lack of privacy, many users decline to share their data.

To train an AI with good efficiency, the first and foremost requirement is lots of data. If an AI is trained with low number of data, it may give high accuracy at the moment. However, when it starts to work with a large number of data, the AI will give lower accuracy. To avoid this, the ML needs to be trained with high number of data from the start. Moreover, in medical sector, patients & medical institutes aren't willing to share medical records for any purpose. This way whenever an AI needs to be trained for medical purpose, a proper training fails to take place due to the lack of available data. To counter these problem, federated learning was introduced.

Federated learning is novel architecture for training ML algorithms without having to collect user private data form their devices. With Federated learning, the machine learning algorithm is sent to client's local device for training with local data. This model is sent to thousands of client's devices. While in the device, this model trains itself using the user's private data in background. When the model has been trained, that model is sent back to the central server. This way the user data never leaves the device nor any private info gets leaked during the training. Only the

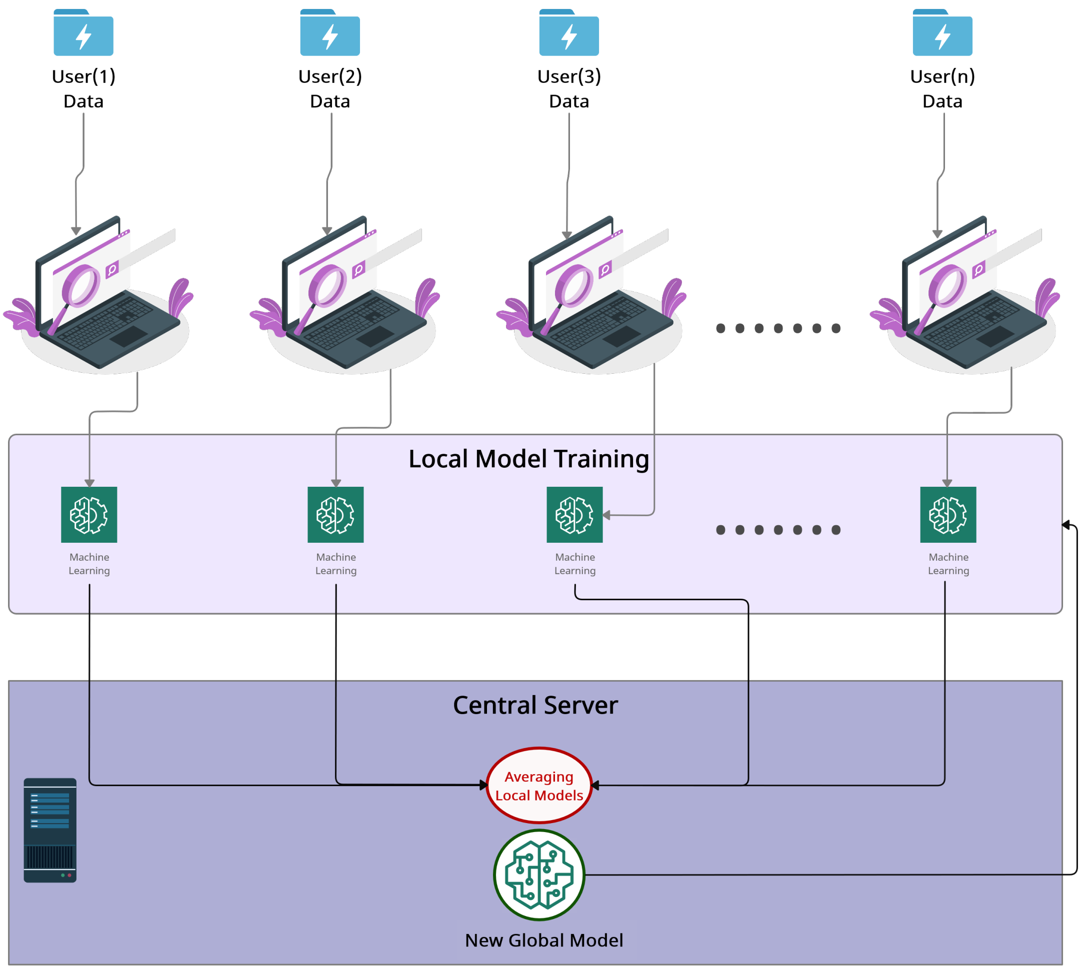

Figure 3.1: Federated Learning

model and the weighted gradients get sent back to the server. When a desired number of local models is gathered at the central server, the central server initiates an averaging method on those local models to create a single superior global model. After that, this global model gets sent to thousands of client's local machines for further training. This cycle continues until a desired accuracy is achieved through training. This way the client's private data stays private while getting to work with a large number of data.

Currently the only practical application that is using federated learning is the google keyboard. Google keyboard suggests query when something is written on it. This information is stored on the phone & helps train a local model. Federated learning then suggests improvements for the next iteration of google keyboards suggestion model. When google used federated learning for the first time, they faced some difficulties such as using typical Stochastic Gradient Descent (SGD) proved to be inefficient [52]. They compensated for that using their own federated averaging algorithm. Recently google has introduced TensorFlow Federated, making the framework more user-friendly.

3.2.1 Federated Learning Framework

In our case the federated framework is going to be used for several medical institutions. To understanding the process of federated learning, lets assume that we have 20 medical institutes containing several local devices each. At the very beginning, the central server of the federated learning broadcasts the initial global parameters. After that, all the devices from each of the medical institute aggregates the local models with local datasets. To get the local weighted gradients in the local devices, the importance factor of each hospital, which is the number of contributions of a hospital vs total contribution of all the hospitals, gets multiplied by the model parameters of the same hospital. The aggregated local parameters then get send to the central server. The central server aggregates these local parameters & updates the global parameters. This is achieved by the central server finding out the mean value of the weighted parameters of all the local models using FedAvg. Lastly, the aggregated new model with new gradients gets send back to each local device.

3.2.2 Types of Averaging Algorithms In FL

FedSGD

In deep learning, Stochastic Gradient Descent (SGD) had demonstrated promising results. The researchers have chosen SGD as a starting point for the Federated Learning training method. SGD is used naturally in the federated for optimization problem, where each round of communication involves a single batch gradient computation (for example a randomly selected client). Instead of computing for all training samples at each step of gradient descent, SGD chooses a small subset (mini-batch) of training samples at random. For global model [53], for each client k, the average gradient on its global model is determined.

$$F_k(w) = \frac{1}{n_k} \sum_{i \epsilon P_k} f_i(w)$$

$$g_k = \nabla F_k(w_t)$$

Then the global server aggregates the new gradients and updates them.

$$w_{t+1} \leftarrow w_t - \eta \sum_{k=1}^{K} \frac{n_k}{n} g_k$$

FedAvg

FedAvg is a slight variation of FedSDG. In FedAvg, the global server takes the weighted average of the resultant models after each client performs one round of gradient descent with the current model by using it on the local data. By iterating the local update numerous times before performing the averaging on global server, extra processing can be added to each client. The number of computations is directed by three parameters [53].

$$\forall k, w_{t+1}^k \leftarrow w_t - \eta g_k$$

$$w_{t+1} \leftarrow \eta \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^{k}$$

q-FedAvg

In [54] a new improved federated learning approach has been proposed. Q-FFL (q-Fair Federated Learning), a uniform way to distribute fair accuracy in the federated network. It reduces and aggregates re-weighted loss so that higher relative weight can be assigned to devices with higher loss & low participation. Q-FFL measures the degree of consistency in performance across devices to generalize standard accuracy parity. Thus, accuracy distribution in the network shifts towards uniformity. To achieve this, they also propose q-FedAvg, a relatively lightweight distribution method for large federated networks which can reach the goal more quickly than baseline FedAvg.

3.2.3 Opportunities

Federated learning opens up new possibilities & opportunities in the tech industry. Some examples are,

Data Based Service

Services that rely on large number of user data to be present in central server, can now provide server on a larger scale without compromising privacy.

Cloud Computing

With federated learning, cloud computing can now provide more AI services without having a central data center.

Data Collaboration

Federated learning can create opportunities for different organizations in the same field to use AI related services without sharing their data with each other. With federated learning, they can create services or AI models in collaboration. In [55], two types of collaboration are stated. There is vertical federated learning and another one is horizontal FL. For example, two telecommunication company can have similar business model while having different clients. With similar business model, they can use federated learning on their client's data and use the outcome to their benefit. This collaboration can is called horizontal FL. On the other hand, if the two company don't have similar service model but have a large intersection of clients, their collaboration with federated learning will be called vertical federated learning.

3.2.4 Challenges of Federated learning

Federated learning comes with its fair share of problems. Every system has minor to major drawbacks, federated learning is no different. The main focus of federated learning is preserving privacy of the user's data. Even though, the user data is not

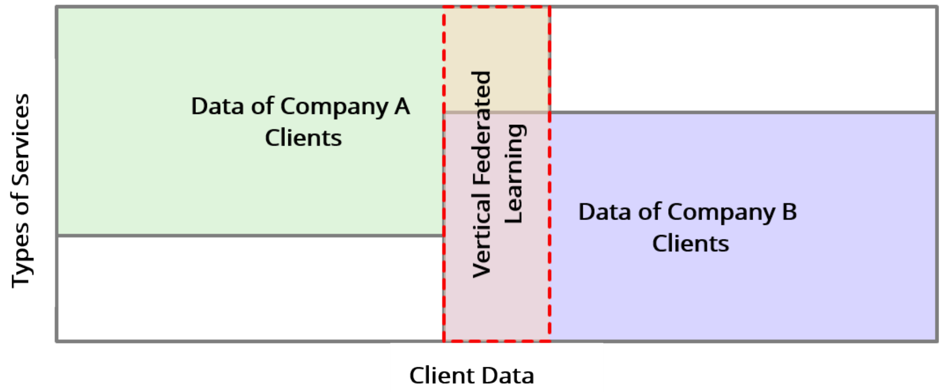

Figure : Horizontal Federated Learning

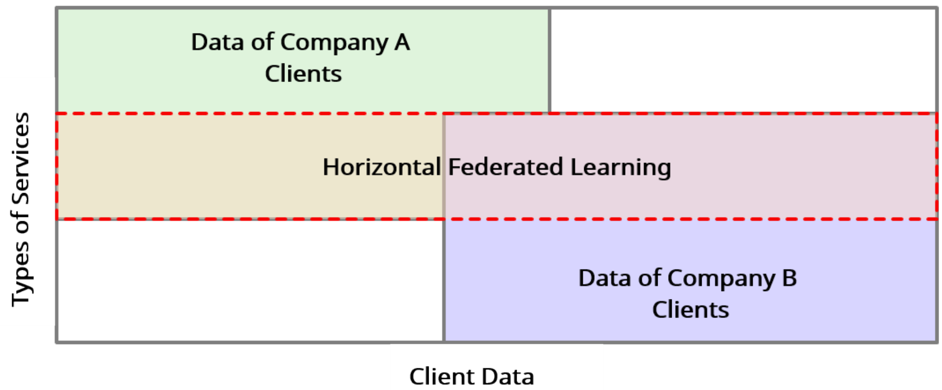

Figure : Vertical Federated Learning

Figure 3.2: Types of Data Collaboration

getting leaked, the local model's weights can be tempered with, resulting in poisoning the global model. To counter this type of attack, blockchain can be introduced into the system.

3.3 Blockchain

3.3.1 Evolution of Blockchain

In 2008, a person using the pseudonym Satoshi Nakamoto first proposed Bitcoin and the blockchain [56], he demonstrated how encryption and an open distributed ledger might be combined to build a digital currency application. At first, bitcoin's exceptionally high volatility and widespread opposition from many nations slowed its development, but the benefits of blockchain technology which had been underlying technology that bitcoin uses garnered growing attention as the cryptocurrency's popularity grew [57].

There is a slew of advantages to blockchain technology, including a distributed ledger system, information transparency, decentralization, tamper-proof architecture, and openness, to name just a few. In the case of blockchain technology, it has been a slow and steady process of development. Blockchain is now classified into three versions. These are Blockchain 1.0, Blockchain 2.0, and Blockchain 3.0, which differ in terms of their applicability [57]. Since its inception as a digital currency, blockchain technology has been used in a variety of financial transactions, and it has even made [57] its way into fields such as health care [58], smart energy, supply chain management, copyright protection etc.

Researchers from a diverse variety of academic disciplines have looked at the potential of blockchain technology. Some academics, for example, have delved at the blockchain's underlying technology, which includes smart contracts, distributed storage, cryptography, and consensus mechanisms among other things. Due to the fact that blockchain technology allows for trustless networks, parties can trade even if they do not have trust in one another [59], blockchain continues to pique the interest of researchers. Without a dependable mediator, disagreements between transacting parties are resolved more quickly. The broad use of cryptography, a critical component of blockchain networks, endows all network interactions with authority. Smart contracts, which are self-executing scripts [59] recorded on the blockchain, combine these concepts and enable the creation of proper, well mentained and automated workflows.

In addition to economic benefits, the blockchain has the potential to provide benefits in other sectors such as politics, [60] humanitarian aid, social welfare, and science. In order to address real-world challenges, specialized parties are presently utilizing the technological capabilities of the blockchain. By utilizing blockchain technology to simplify transaction and settlement processes, costs associated with manual operations can be significantly reduced. For example, in the health-care industry, blockchain technology can be crucial in centralized research data storage, combating prescription medication fraud, and cutting administrative expenses, among other things [58]. As a layer of trust between untrusted parties is built, safe and trusted records and transactions may be recorded and transacted on the blockchain, allowing for the recording and transacting of financial transactions. It is necessary to engage a third-party intermediary if Blockchain is not used to create accurate records and transactions in order to avoid this situation. Through encryption and cooperation, blockchain builds confidence in transactions, removing the need for a centralized institution to act as a middleman in the transaction process. The Blockchain, which is a public ledger, stores information using cryptography, which is protected by a password.

With the advent of blockchain technology, the quality and availability of copyright data in the music business, as well as the transparency of the value chain, have the potential to significantly improve. [60] Using four example applications, the economic value of block chain is demonstrated: long-tail tailored economic services, digital asset registries, and leapfrog technologies, payment channels, and peer banking (as well as other applications).

3.3.2 What is Blockchain?

A blockchain, in its simplest form, is a public ledger or database of all transactions and digital events that has been shared with those who have participated. In order for a transaction to be considered valid, it has to be recorded on the public ledger and then accepted by the majority of the users of the system. As soon as a user enters data, it cannot be removed. On the blockchain, each transaction is unique and tamper-proof. An analogy is that it is simpler to get your hands on some cookies at a secluded spot than to get your hands on some cookies in the middle of the market when thousands of people are looking [61].

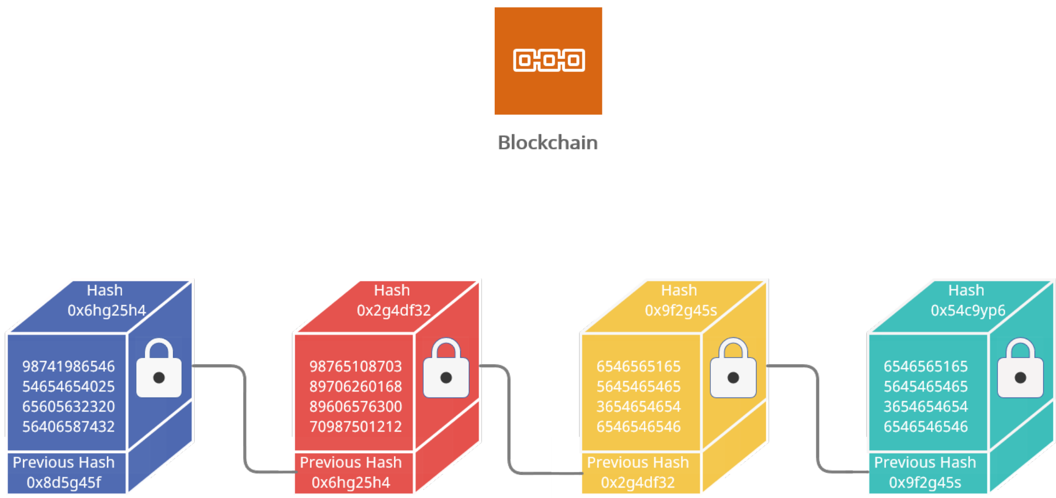

Figure 3.3: Blockchain

This decentralized storage system operates without the intervention of decentralized network that operates independently of any central authority and stores data in blocks linked together by the cryptographic hash of the block before it. Blockchain is a decentralized storage system that operates independently of a central authority [62]. The blockchain stores data in the form of blocks that are connected to create an immutable chain. When a new transaction is added to the blockchain, the ledger is immediately updated, and a notification of the transaction is sent out to all of the peers in the network.

3.3.3 Consensus Algorithms of Blockchain

As a distributed decentralized network, blockchain ensures immutability while also protecting user privacy and security. On the Blockchain, transactions are completely safe and authenticated despite the fact that there is no central authority in place to approve or deny them. This is only feasible because of the consensus process, a vital part of any Blockchain network. When all of the peers in a Blockchain network establish a shared understanding about the current state of the distributed ledger, this is referred to as a "consensus algorithm" or "distributed ledger consensus algorithm." Consensus algorithms, on the other hand, help to keep the Blockchain network reliable and build trust between people who don't know each other. Every time a new block is added to the Blockchain, the consensus protocol makes sure that it's the only version of the truth that has been agreed to by all of the nodes. . As part of the Blockchain consensus protocol, all miners in networks has same power and must participate on consensus process in order to come to an agreement, collaborate, and cooperate. The goal of consensus algorithms is to find a common agreement that benefits the whole network.

3.3.4 Proof of Work

Nodes in an environment where they do not trust one another are the primary purpose of a process for consensus. Adding a new block to the blockchain requires verifying all of the transactions in that new block before adding it to the overall ledger. Proof-of-Work is the term used to describe the process by which miners solve a complex mathematical problem for connecting a newly block with other blocks. As time goes on, the arithmetic problem becomes increasingly complex. Validating the transactions in a block before it is added to the network, sorting them into chronological order, and making the freshly mined block known to everyone takes some time and effort.
To add a new block to an existing blockchain, one must first solve an extraordinarily tough problem. The Proof of Work algorithm is used by several cryptocurrencies, including Bitcoin, Litecoin, ZCash, Primecoin, Monero, and Vertcoin. The hash value obtained by the Bitcoin algorithm is randomly altered using the nonce. In the Bitcoin consensus algorithm, the hash value is generated using a parameter called the nonce. Proving one's work (PoW) has had an impact not just on financial institutions but also on the health care and governance sectors. Multi-signature transactions and multi-channel payments over an address have been made possible as a result of this technology

3.3.5 Practical Byzantine Fault Tolerance (PBFT)

In order to solve the concerns of the Byzantine General, PBFT is a lightweight blockchain approach that enables users to ensure that consumers are aware of the communications they have received by performing a calculation to check the validity decision. When a party makes a choice, it broadcasts it to other nodes, who subsequently implement it. It is therefore decided by what other nodes have to say about the final decision. Stellar, Ripple, and Hyperledger Fabric are examples of blockchain consensus mechanisms that make use of this method.

3.3.6 Proof of Stake

This is the variant of PoW that is most often seen by users. A Proof-of-Stake consensus has been established in Ethereum, replacing the previous proof of work consensus. As an alternative to investing in expensive equipment to solve a hard task, validators make an investment in the currencies of the system by holding on to a percentage of their coins as a stake in the system. As soon as it happens, all of the validators will start checking the blocks in the sequence in which they were received. Validators who come across a block that they feel can be added to the chain will validate it by putting a wager on the block in order to validate it. The rewards for validators are determined by the actual blocks that are added to the Blockchain, and their stakes rise in proportion to the rewards. Validators are chosen at the end of the procedure to create a new block on the basis of how much money they have invested in the network as a whole. As a consequence, via the application of an incentive mechanism, the Proof of Stake promotes validators to achieve a consensus on a transaction.

3.3.7 Proof of Elapsed Time

Proof of Elapsed Time is one of the most equitable consensus algorithms known, picking the next block based entirely on its fairness. It is often used in permissioned Blockchain networks, where its high level of security makes it ideal. Under the conditions of this approach, any validator on the network has an equal chance of generating their own block. For this, each node waits a random period of time before reporting their delay in the block. For the rest of the network, the blocks that have been formed are sent out for consideration. During the game's proof phase, the validator with the lowest timer value is declared the winner. A new block is uploaded to the Blockchain when a validator node wins a contest. An additional set of checks is introduced into the algorithm to prevent nodes from always winning elections and from producing the timer value with the lowest possible feasibility.

3.3.8 Blockchain based Federated Learning

Security issue has been an emerging drawback especially in healthcare industry. In terms of security FL can also experience potential data and information leakage or poisoning attacks. Because in the FL each client server computes training gradients in their own server and from those servers, the trained gradients go for central server. But there can be varieties of data distribution in each client server as distributed learning algorithms. When those gradients from client server's approach for central server for federated averaging, in the pathway from client servers to central servers there can be possible threats of data revealing or breaching. For eradicating this issue, Blockchain going to play the magnificent role in FL. Between client servers to Central server in the middle pathway there going to be blocks and for each transactions of gradients one block going to be added with previous blocks also from central server after federated averaging all the updated gradients going to return their each client servers through the blocks of each transactions in this way Blockchain eradicates Fl security issues. Another security issues Fl faces in each client server's training period in the time of weighted averaging, there are lots of security breaks occurs which reveals lots of information from user's, it can leak information's like levels distribution or class distribution or images related to sick or healthy peoples. Blockchain also eradicates this security breaches because when this information leaks outside from the filter it stays in the blocks of chain so, these prospective threats can also resolve through Blockchain. The primary benefits of Blockchain are security and anonymity, which enable users to provide decentralized proofs of documents that cannot be altered by a third party [61], the document's existence is verified using blockchain technology, which is decentralized and does not rely on a single centralized organization.

3.4 Activation Functions

3.4.1 Adam

Adaptive learning rate optimization approach by t raining deep neural networks has never been easier than using Adam, a new method created just for that purpose. The algorithms take use of the capabilities of adaptive learning rate techniques in order to calculate individual learning rates for every parameter in the model. Adagrad, which performs remarkably well in situations with sparse gradients but suffers in non-convex optimization of neural networks, as well as RMSprop, which seeks to solve some of the flaws with Adagrad, are also included as benefits of the approach. The authors [63] introduced Adam, a stochastic optimization strategy that only employs first-order gradients and requires less memory. In addition, The term Adam is derived from the adaptive moment estimate and is used to construct individual adaptive learning rates for different parameters utilizing estimations of the first and second moments of the gradients. Their [63] solution combines the benefits of AdaGrad and RMSProp, two newly recognized algorithms that perform well for sparse ingredients. We utilized an upgraded variant of stochastic gradient descent with an epsilon of 0.0001 and a learning rate of $1e^5$ to train the network for maximum accuracy.

3.4.2 ReLu

As our data is nonlinear, which implies that we will be able to effectively back-propagate the errors, and because we have numerous layers of neurons, we have employed the ReLu activation function inside the mid-layer of the network. When building multilayer Perceptron and CNN networks, the rectified linear activation is utilized as the default activation. ReLu is capable of converting between linear and non-linear forms. It is applied in the hidden layer to create testing accuracy for the testing procedure. It depicts as, $f(x) = max(0; x) \rightarrow$ It sets everything less than 0 and retains everything else the same as > 0.

3.4.3 Softmax

Softmax activation happens as a consequence of a multi-class probability distribution across the target classes. The softmax function is given numerically below, where z, I signifies the inputs to the output layer. In addition, the output units are indicated by the variable j, which has values of $j = 1, 2, ..., K$.

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

3.4.4 Loss Function

In order to build and design our proposed model, neural networks require a loss function and are ready to use stochastic gradient descent. Categorical Cross entropy loss function has been used to achieve data equilibrium. It is employed in the optimization of classification models for multi-class classification. In machine learning, the probability difference between 0 and 1 is calculated using this value.

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

3.5 Data Augmentation

Image augmentation is the process of altering images that are already in a training dataset in order to produce many versions of the same image that are somewhat different. This not only offers us extra images to train on but also exposes our classifier to a greater variety of lighting and coloring circumstances, making it more robust. We used to flip and histogram equalization. One of the most common techniques to get extra data for a classifier is to flip photos horizontally. Histogram Equalization improves visual contrast by recognizing and displaying the distribution of pixel densities in an image on a histogram. The distribution of this histogram is then evaluated, and if there are ranges of pixel brightness that aren't currently being used, the histogram is extended to span those ranges before being again projected onto the image to boost overall contrast.

3.6 Image Processing

Image Processing entails the systematic use of various algorithmic algorithms to image data to enhance the image and extract necessary data from it. It could be a form of banner creation in which the input signal is an image, and the output signal may be an image or attributes associated with that image. This refinement is one of the rapidly improving advantages, and it also shapes middle-school inquiries regarding region interior design and computer science guidelines. To be precise, there are two types of image processing plans: analogue and digital image processing. While performing these visual methods, image investigators employ a variety of transnational fundamentals. Computerized image processing techniques assist in managing developed images through the use of computers. All data types require familiarization at three typical stages when using a computerized strategy. These strategies are upgrade, pre-refinement, presentation or data emotion. The fundamental steps involved in any type of image manipulation are as follows,

1. Establish the input picture through the use of procurement tools

2. Analyze and maintain control over the image

3. Obtain the produced image or the outcome of the input image examination

Processing of Digital Images

Digital image processing is manipulating images with the aid of a sophisticated device. Pre-processing, augmentation, and display are the three standard levels that all types of data should be experienced while utilizing digital technologies. Extraction. In digital image processing, three distinct forms of processing are used. There are three types of image processing. These levels are low-level image processing, intermediate-level picture processing and lastly high-level image processing.

Image Processing at Pixel Level

Low-level image processing is usually used when the inputs and outputs are images. It includes noise reduction, comparison enhancement, and image sharpening.

Image Processing at Intermediate Level

The term "middle-level image processing" refers to image processing in which the inputs are images, but the outputs are image attributes. It encompasses a variety of responsibilities, including picture segmentation, classification, and recognition.

Image Processing at A High Level

Lastly "high-level image processing" refers to the type of image processing in which the inputs are not widely credited, but the results are. It entails duties that make sense based on a collection of recognized elements.

Digital Image Processing Stages

Digital image processing is divided into seven stages. They are,

1. Image capture
2. Enhancement of images
3. Restored image
4. Morphological transformation
5. Categorization
6. Recognition of Objects
7. Representation and Description of Images

Image Capture

It is the technique of obtaining an entirely unprocessed image to portray an object's visual features. This stage is the initial stage, and it typically comprises pre-processing. There are many types of image capture in today's era.

Enhancement of Images

Image enhancement is a method that use picture filtering in order to improve the quality of an image, and it is concerned with reducing noise and enhancing brightness or sharpness.

Restoring Images

Image restoration is repairing the portion of the image that contributes to the image's deformity. It is the technique of enhancing an image using mathematical models, for example, by reducing blur from an image.

Morphological Transformation

It is the process of representing visuals in a variety of decision-making contexts. The process of converting a unprocessed gray-scale image to a binary image in which each pixel has a specific value of 0 or 1 is referred to as morphological image processing.

Categorization

It is a technique for segmenting one image into several segments. Image segmentation is a technique for separating a digitized image into various fragments or sets of pixels in order to transform it into something more significant and less laborious to evaluate. It is used to determine the borders or objects in a given image. In other words, picture segmentation assigns a name to each pixel, ensuring that pixels with identical names share comparable features.

Recognition of Objects

Object recognition is a technique for labelling objects. Object recognition algorithms are used in digital image processing to identify and recognize objects in a given image. Numerous models can be used for object identification, that includes machine learning models, feature extraction and deep learning models like CNN, derivative-based and gradient-based coordination techniques.

Representation and Description of Images

This is the final step in the processing of digital images. After an image has been effectively portioned and all of its objects & foundations have been separated, it is crucial to refer to the objects correctly using their precise characteristics. It entails representing an image in a variety of ways,

- Boundary Representation: It considers exterior shape characteristics such as corners and inflexions.
- Regional Representation: It emphasizes both internal and external features and surface and skeleton shape.

3.6.1 Techniques for Neuroimaging

Neuroimaging techniques are critical in evaluating patients because they can detect abnormal brain states. When neural impulses increase, there is an increased oxygen consumption in the brain and the immediate reaction is an increase in blood flow to areas of increased brain activity. FMRI now has a minor but growing role in medical neuroimaging, and it has long been used in pre-surgical planning to constrain brain features. Functional MRI employs the blood oxygen level subordinate (Bold) approach to depict neuronal mobility rather than axonal acuity, identifying deviations from the utilitarian organizes the norm rather than the auxiliary organizes standard [64].

Neuroimaging approaches can be classified into two categories,

Imaging of Structural Elements

Structural imaging uses the brain's structure to ascertain the presence of a large-scale illness.

Functional Imaging

Functional imaging enables visualization of the brain's data since movement within the brain's included range increases the digesting system.
These images are the product of an excellent type of fMRI effort. While reclining in the MRI machine, the participant discovered a display alternating between displaying a visual improvement and being dull every 30 seconds.

3.6.2 Brain Imaging for Parkinson Detection

Cranial CT can reveal normal pressure hydrocephalus in parkinsonian individuals with short stepped gait, freezing, and instability. MRI can diagnose degenerative parkinsonism. No marker has been established for the signal void in Parkinson's disease's substantia nigra. MRI is mostly used for detecting PD and atypical parkinsonism. Also some structural MRI abnormalities are specific and indicative of multisystem atrophy, corticobasal degeneration and many other. Sensitivity is normally 60-80%. Three to five mm thick slices were 80% sensitive to striatal signal intensity changes in PMS. However, while improved MR volumetry methods have been used to discriminate between PD, multisystem atrophy, and progressive supranuclear palsy. Parkinsonian striatums had lowered the ratio between N-acetyl-aspartate and creatinine. There are several similatities between idiopathic PD and multisystem atrophy. The intact striatum is thought to distinguish atypical parkinsonian diseases from Parkinson's disease. First studies demonstrate putamen regional diffusion coefficient variations are sensitive and selective for discriminating illnesses. Diffusion-weighted MRI may be a useful routine parameter in early Parkinson's disease differentiation [43].

Chapter 4

Methodology

4.1 Work Plan

The purpose of the Blockchain-based FL is to detect PD by protecting the privacy and security of client's data. To train a machine learning model using FL, several people may do so without having to share their local data. Federated learning involves data protection. Federated learning ensures that data can be used even if it is kept on a local computing device. Furthermore, federated model training can be harmed by a model poisoning assault.
To solve these issues, we're utilizing Blockchain in a federated learning model. Designing a process that receives data from four client servers as an input, systematically analyzes data and delivers the gradients to a central server where Fed averaging updates the gradients then send them back via blocks to client servers which is required in order for this model to work. It is when clients will find out if they have PD or not. Figure 4.1, shows the model design. PD Detection process through Blockchain base FL is the process that is responsible for preprocessing input data, training and Fed Averaging. It has three major stages,

1. Input data preprocessing: this is the stage which is concerned with formatting input data to make it easier for clustering, processing, and testing in training data.

2. Training Data: this is the stage where input data is processed, a trained model is built, and the model is tested.

3. Fed Averaging: this stage is the central server where the gradients coming from the trained model through blocks will be updated through the Fed Avg algorithm.

Each server communicates with the central server by transmitting an epoch for a specific length of time. The Fed Average Algorithm is used by the central server to provide updated gradients back to the local client-servers. Each server sends data to the central server and each transaction is added to the Blockchain, creating a federated learning paradigm. Using the proof of concept, Blockchain transactions will be verified.

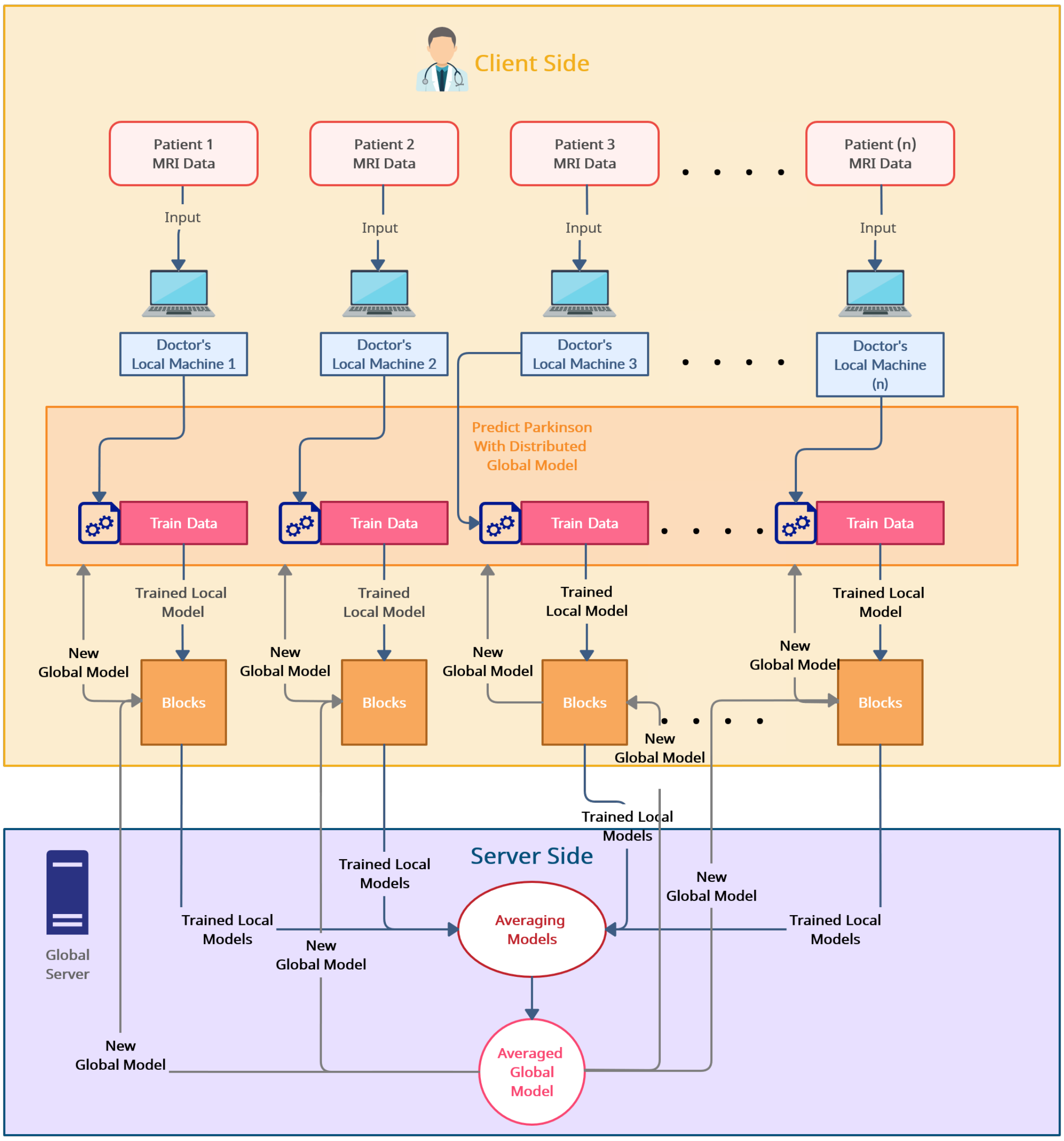

Figure 4.1: Flow chart of the proposed Blockchain based FL

4.1.1 Input Data Collection

We used FP-CIT SPECT (Single-photon emission computed tomography) data received via approved access from the Parkinson's Progression Markers Initiative (PPMI) [65]. Any –up-to-date data may be obtained from [65] through data access request. PPMI is a major research objective to find biological markers, initiation and development of Parkinson Disease which was founded in 2010. They give open-access data set and biosample library of PD including FP-CIT SPECT (Single-photon emission computed tomography) and MRI. In this study we are going to employ SPECT. The collection comprises of 645 subject's FP-CIT SPECT pictures. With 207 healthy individuals (HC) and 434 people with Parkinson's disease (PD) taking part. Following the collection of raw data, PPMI uses an iterative ordered-subsets-expectation-maximization method in their lab to rebuild the center picture on HERMIS workstation (a medical imaging computer).

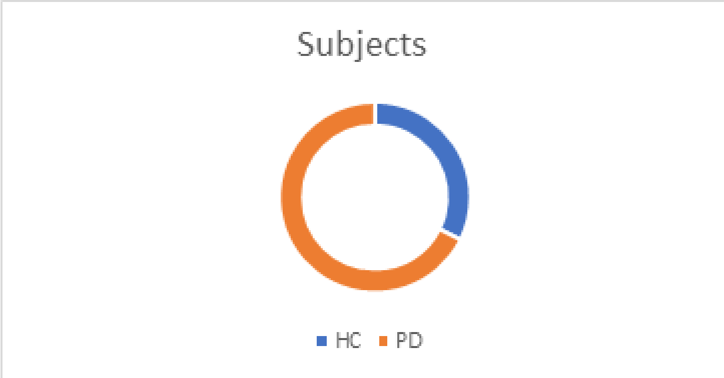

Figure 4.2: PD & HC Diagram

The data in dataset has two states. One is Resting state, another one is BOLD (blood-oxygen-level dependent) state. In resting state, the brain is kept idle or task negative state while mapping. In BOLD state where brain mapping is done even when external prompted task is absence.

4.1.2 Data pre-processing

Data preprocessing is a challenging aspect as it requires the right attributes to be used to do a relevant analysis.
We employed computed tomography with a limited multifaceted resolution and an anisotropic Gaussian filter with an 18 mm FWHM to construct FP-CIT single-photon emission for early data preprocessing) to every one of the initial 3D PPMI SPECT image. This process allowed us to smoothen images for the SPECT images and prep the data accordingly for image classification later. There are three distinct techniques for the creation of the PPMI settings. These are,

1. Original, unsmoothed images, which include around 438 Parkinson's disease affected patients, and 207 healthy patients.
2. Smoothed images including 438 Parkinson's disease patients, and 207 Healthy patients.
3. Then we have the mixed setting, which included both original and all the smoothed pictures, including 414 Healthy Patients and 876 Parkinson's disease patients [66].

A total of two hundred and ninety-eight patients who had been under regular clinical assistance in University Medical Center Hamburg Eppendorf were selected at random from the database. The patients were grouped into two based on the following characteristics: Group A: patients with neurodegenerative PS and patients without it, Group B: patients who have non-neurodegenerative PS. The group A patients, which was a total of 149 patients, with 46.3 percent female of the age group 64.9 years with a wide range of ± 10.7 years. Lewy body disease spectrum (132 patients, making 88.6% of total) and Parkinson's disease and Parkinson's disease dementia and Atypical Parkinsonian syndromes (comprising 17 patients making the 11.4% of the total); these patients also had multiple systems atrophy and progressive supranuclear palsy. For patients in Group B (149 in total), which comprised patients with different illnesses other than nigrostriatal degeneration and who were in the age range of 66.2 years or older, the gender distribution was 50.3% female and the age range ranged from 11.8 years. During the review of all 149 patients with neurodegenerative PS (average review period of 41 months with an additional bounding period of 23 months, range 13–96 months) and 44 patients with non-neurodegenerative PS (average review period of 38 months with a different bounding period of 22 months, range 13–96 months). In order to maintain stability in the remaining 105 patients with non-neurodegenerative parkinsonian disorders, we included them in the study. In accordance with conventional protocols, FP-CIT SPECT was carried out utilizing a dual-head system [67], using a dual-head SPECT system (Siemens Symbia T2 or Siemens E.CAM). Reconstruction procedures were employed in each situation in a different way. SPECT images were initially reconstructed using filtered back projection (Butterworth filter of fifth order, cutoff 0.6 cycles/pixel) in the SPECT system software implementation. After using Chang's (=0.12/cm) uniform post-reconstruction attenuation correction, no further scatter correction was required. We used HybridRecon-Neurology to produce the images using the Hermes-recommendation parameters (80 iterations, 7 mm full width at half maximum, uniform post filtering) and the ordered subsets–expectation maximization technique to generate the images. The corresponding author may offer the clinical sample's FP-CIT SPECT data upon request.

Chapter 5

Implementation

Once the data has been processed, we feed the data to VGG16, VGG19 and InceptionV3 model to get accuracy of PD classification. We also used Adam as an optimizer to reduce workload and computation time. Adam is a combination of AdaGard and RMSProp resulting in better optimization. We used 800 MRI slice for training prediction model and 600 for test our model's accuracy. Here are some images we used.

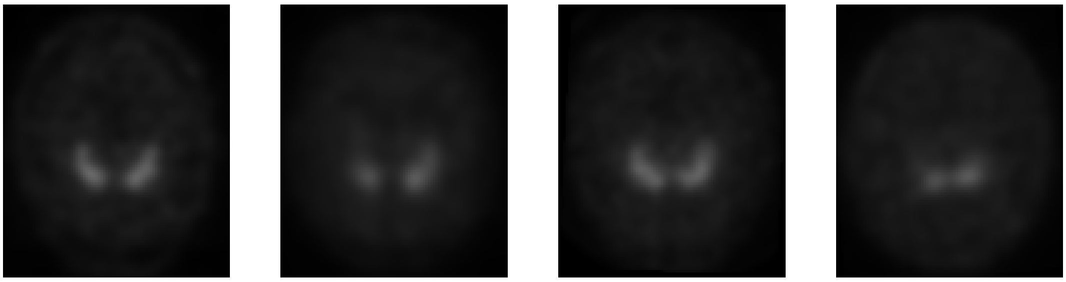

Figure 5.1: From left to right, Train HC, Train PD, Test HC, Test PD

The image shown above are the results after the dataset was split. From the three model we different results with different accuracy. On our dataset, we have used

three CNN architectures for classification: the VGG19, the VGG16, and the InceptionV3.

5.1 Algorithms

Bellow are the algorithms that are used for testing accuracy of Parkinson's decease prediction in federated learning environment. These are VGG19, VGG16, and InceptionV3.

5.1.1 VGG19

The VGG19 convolutional neural network introduced by Simonyan and Zisserman [10], comprises of 19 layers, 16 of which are convolution layers and three of which are completely coupled, and it can classify pictures into 1000 distinct object classes. The ImageNet collection was used to train VGG19, which now has over a million pictures organized into more than a thousand distinct categories. Many 3×3 filters are used in each convolutional layer of this image classification algorithm, making it very efficient.

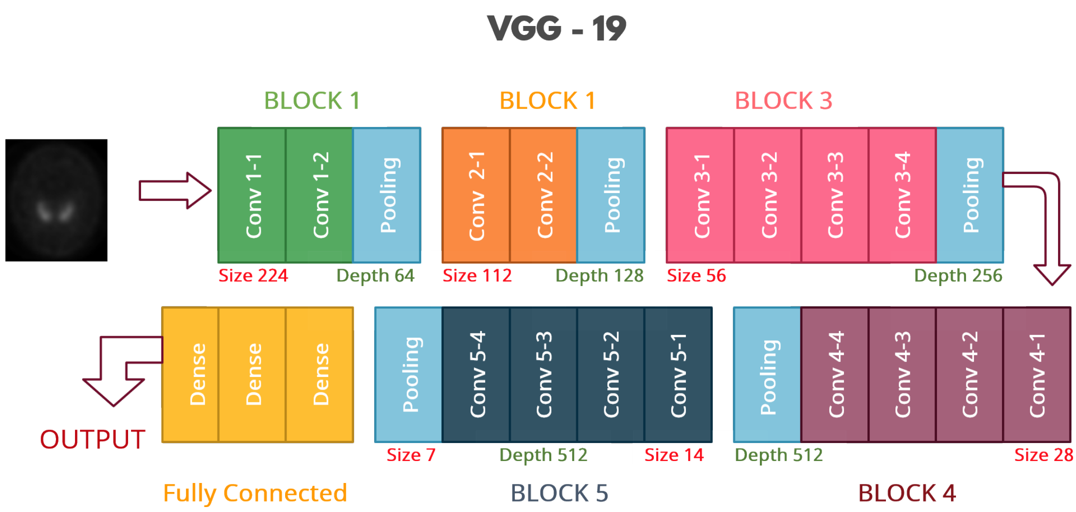

Figure 5.2: VGG19 Architecture [68]

The authors [68], used VGG19(Figure) model for removing false positives in breast cancer detection. Considering that the VGG-19 model accepts a color image as input, a 3-channel image is generated by assigning the colors (current exam, prior exam, difference image) to the channels (red, green, and blue), accordingly. To train and test the VGG-19 model, all regional pictures (derived from the improved region proposal) are cut from the 3-channel image and scaled to 2242243. As a result, small changes over time are reproduced in this 3-channel image and featured in the revised VGG-19 model.

5.1.2 VGG16

VGG16 structure also proposed by [10], VGG-16 is a convolutional neural network with 16 layers of depth that is used in image recognition. The pretrained network can classify images into more than a thousand different types of objects.

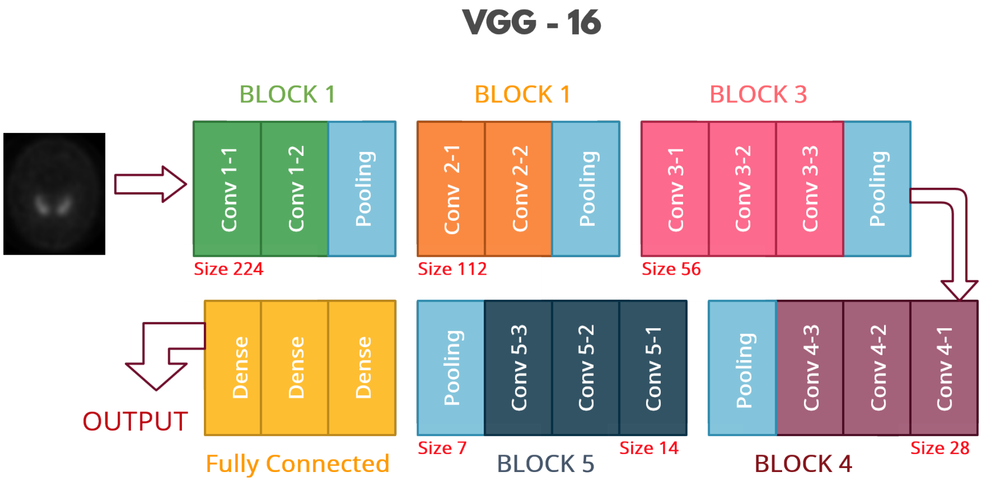

Figure 5.3: VGG16 Architecture [69]

5.1.3 InceptionV3

InceptionV3 is the extended model of [70], the authors found that InceptionV3 model requires less computation with more precise results. Furthermore, this model computes cheaper in terms of performance and also, require fewer parameters. Several different sized convolutional filters are concatenated into a single new filter, which is referred to as a "inception model" in the InceptionV3 model. This style of design decreases the amount of parameters that must be taught, thereby minimizing the computational complexity [63].

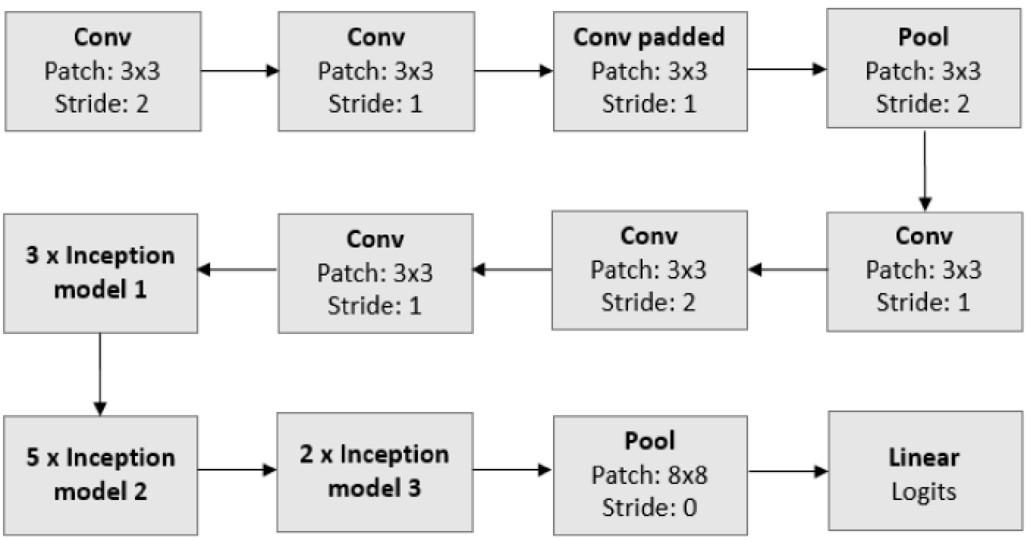

Figure 5.4: InceptionV3 Architecture [69]

5.2 Input Data-Prepossessing

While training a model, data preprocessing is a mandatory prerequisite as the data used in training is usually very large in number. It is the same in our case as well. FT-CIT SPECT images are acquired in form of slices (2D) during an SPECT session. These slices are then combined into one 3D model of the brain. For our training, we are using the 2D slices of affected (PD) and non-affected (HC) people which we separated from the original dataset. After that, we split the data into two sections, train-test and test, each having separated HC and PD sections. For train test, we allocated 85% of the data and for test we allocated 15%. During data visual inspection, some HC and PD scan was excluded due to reduced striatal and normal FT-SIT uptake. After that, the first (unsmoothed) SPECT images were given an isotropic 18-mm Gaussian kernel smoothing, which resulted in the production of three PPMI settings: i) original (unsmoothed), (ii) the smoother image, and (iii) the mixed image (all original and smoothed images). On the basis of the actual three-dimensional SPECT pictures, this creates a simulation of FT-CIT SPECT images with a poor spatial resolution.

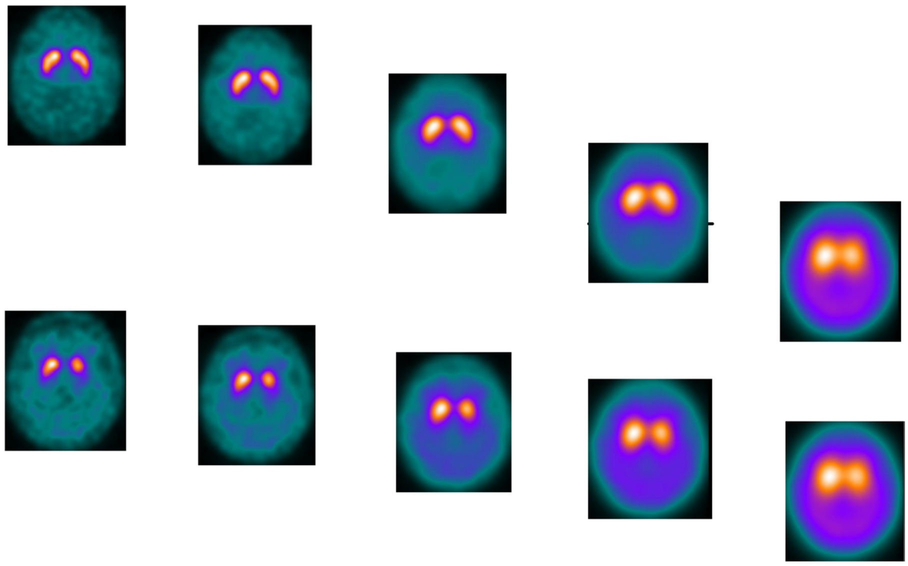

Figure 5.5: SPECT Imaging [20]

5.2.1 Process

We have used TensorFlow Federated for implementing federated learning. The database used here are divided into two categories, one is HC which represents healthy patient and another one is PD, representing the Parkinson affected patients. After this division, the dataset is shuffled and split into test and train category. In the implementation of FL that will take place in the real world, every federated member will have their own data linked with them in isolation. However, in order to conduct this study, we have fabricated five clients and given each of them a random portion of the data shards. The next step is to batch process each individual user's data and import it into a TensorFlow data set. Now for the model, we added the convolution neural network with flattened output. We have also added a dense layer of ReLU. Softmax is also used for the actual classification. For optimizer, Adam is used on the accuracy as the matric. Now for the FL part, vanilla algorithm which is FedAvg is used for averaging. The data we utilized is horizontally partitioned, so we have done component wise parameter averaging which is weighted depending on the percentage of data points given by each of the participating client. Here, we are predicting the weight parameters for every client based on the loss values reported across every data point they trained with. There are three sections to this. First, a percentage is calculated by comparing the total number of training data points collected from all clients with the total number of data points stored by a single client. As a consequence, we now know how much data there is for training throughout the world. The model's weights are scaled in the second section, and the scaled average of the weights is returned in the third section as the sum of the stated scale weights. This is followed by a comparison with a known test dataset to determine the accuracy of the global model.

Now that we are ready to begin the real training session, we will first get the weights of the global model, which will be used as the starting weights for all local models. Next, we will randomize and shuffle the client data. After that, a new local model is built for each client, and that model's weight is adjusted so that it matches the weight of the global model. After that, the local models are calibrated with the client data, and their weights are adjusted so that they may be added to the list. To get the average value across all of the local models, we need to do nothing more complicated than add up all of the weights that have been scaled.

Chapter 6

Results Analysis

We have trained our model with the epoch of 100 for the InceptionV3 model and an epoch of 5 for both the VGG16 & VGG19 models. We have got around ninety-five percent accuracy for all the models.

6.1 Inception V3

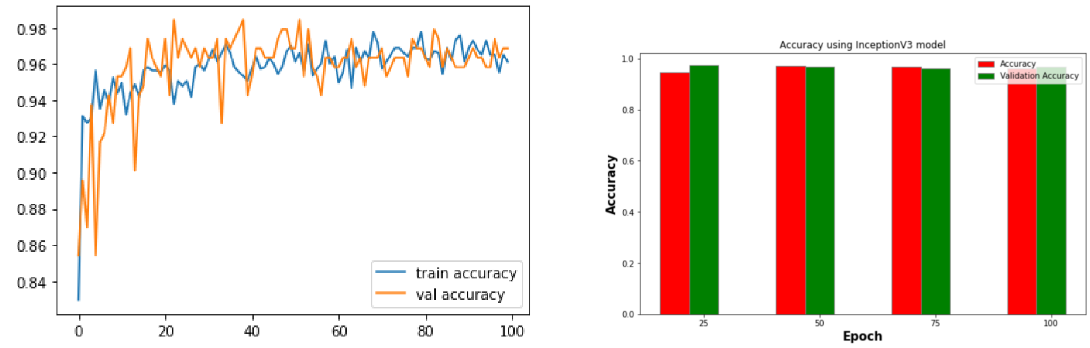

Figure 6.1: Accuracy For Inception V3

When we run 100 epochs in the InceptionV3 architecture for both training and validation, we get about 96% accuracy & validation accuracy. First, we ran the 1st epoch. We got an accuracy of 82%. As the epoch went on, the accuracy went up a lot. It took us until the 100th epoch to get the most accurate results. At that point, we were able to get 96% of the results right.

6.1.1 Loss for Inception V3

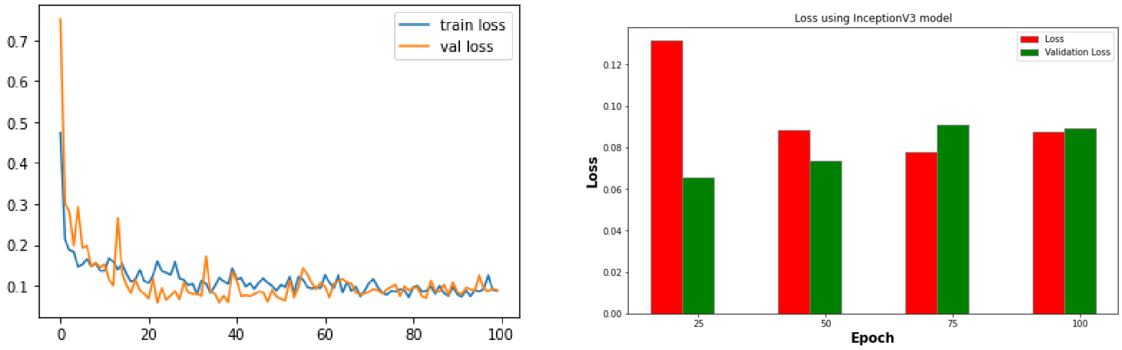

Figure 6.2: Loss for Inception V3

The loss function is important in adjusting the parameters of neural networks to reduce loss. The loss is estimated by comparing the actual value to the expected cost using a neural network. As we observe from the graph, during the 1st epochs we find the loss of 47% and 75% validation loss for InceptionV3. As the epochs grew the loss reduced. Finally, at the 100th epoch, we obtain an 8% decrease for both loss and validation loss.

6.2 VGG16

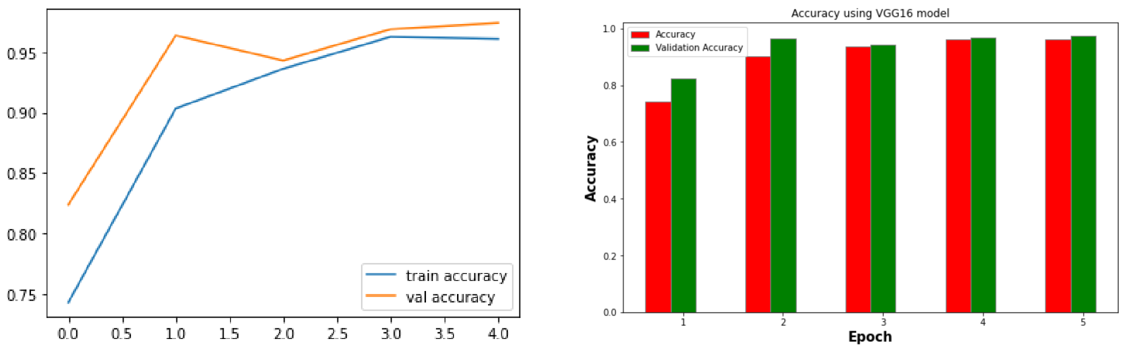

Figure 6.3: Accuracy For VGG16

For training, we can see from the figures above that if we run a total of five epochs in the VGG16 architecture, we get about 96% accuracy & validation accuracy. First, we ran the first epoch. We got a 74% accuracy rate. During our 2nd epoch, we were able to get 90% accuracy. As the epoch went on, the accuracy went up a lot. After running more epochs at the fifth epoch, we were able to get the best accuracy of 96%.

6.2.1 Loss for VGG16

We observe from the graph, that during the 1st epochs we discover the loss of 54% and 40% validation loss for VGG16. As the epochs increased the loss dropped. Finally, at the 5th epoch, we gain a 10% reduction for loss and a 7% validation loss.

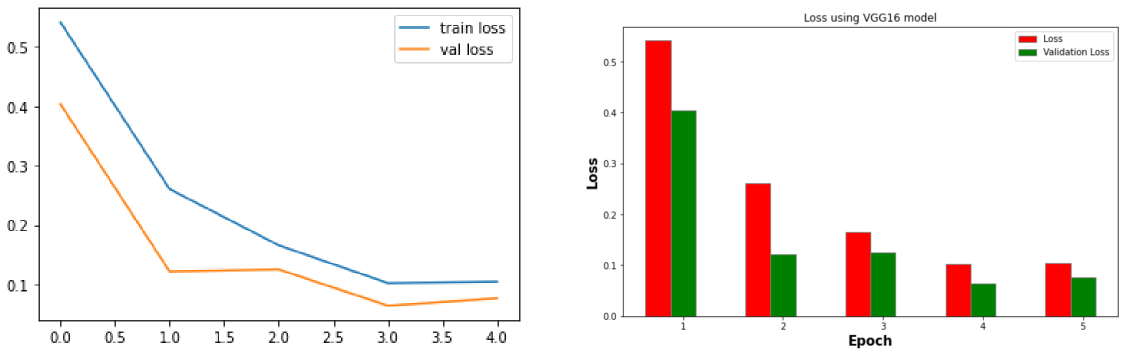

Figure 6.4: Loss for VGG16

6.3 VGG19

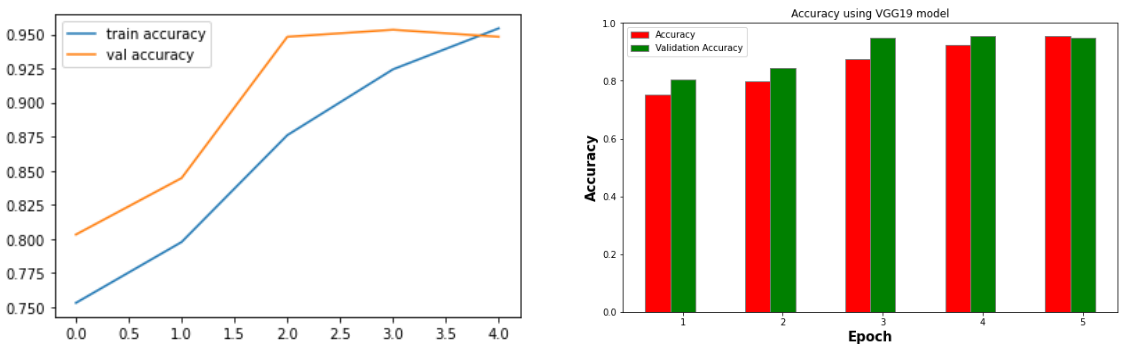

Figure 6.5: Accuracy For VGG19

Here also we run complete 5 epochs in VGG19 architecture for training we got approximately 95% accuracy and validation accuracy. Running the 1st epoch, we got the accuracy of 75%. After performing the 2nd epoch, we achieved an accuracy of 79%. The accuracy substantially rose inside the as the epoch grew. After further running the epochs at the 5th epoch we were able to acquire the most significant accurateness of 95%.

6.3.1 Loss for VGG19

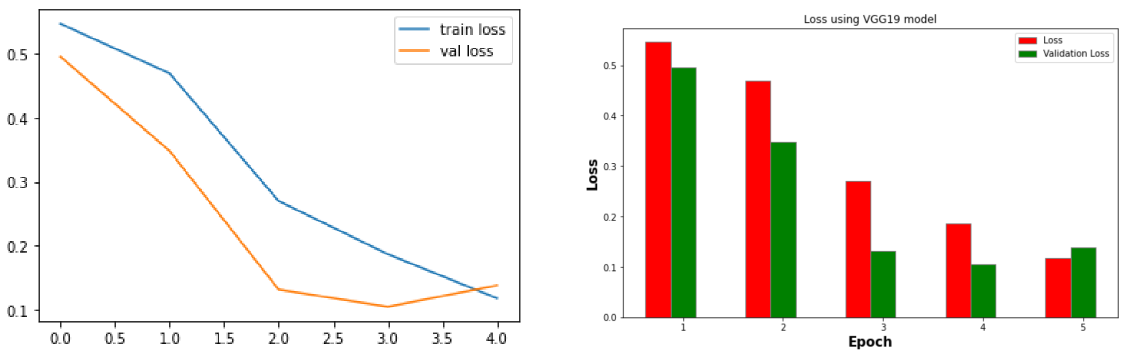

Figure 6.6: Loss for VGG19

We can see from the graph that during the first epochs of VGG19, we had a loss of 54% and 49% of our validation loss. From the second epoch, we found that VGG19 lost 46% and 34% of its validation loss. Finally, at the fifth epoch, we see an 11% drop in loss and a 13% drop in validation loss.

6.4 Discussion

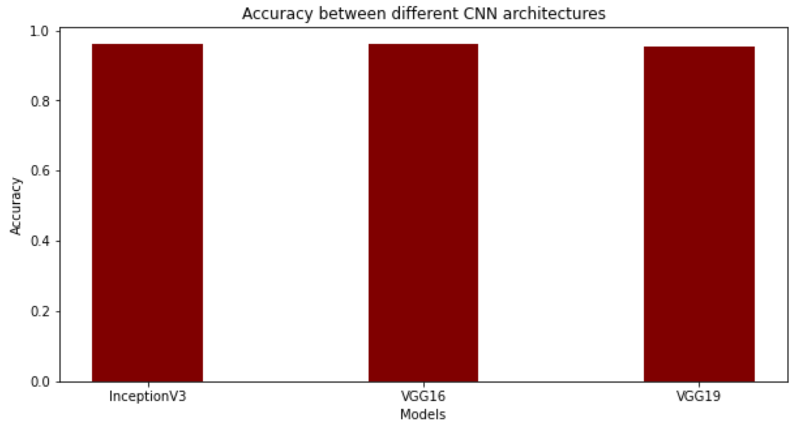

Figure 6.7: Accuracy Between Different CNN Architectures

We can see how the VGG19, VGG16, and InceptionV3 accuracy look side by side. We made the bar graph by taking the best accuracy of the last epoch and making it into a line. Each architecture has its level of accuracy. In the graph, we can see that in the final epoch, VGG19 gives an accuracy of 95%, VGG16 gives an accuracy of 96%, and InceptionV3 gives an epoch accuracy of 96%, which is the best. So, we can say that VGG16 and InceptionV3 architectures did better than VGG19.

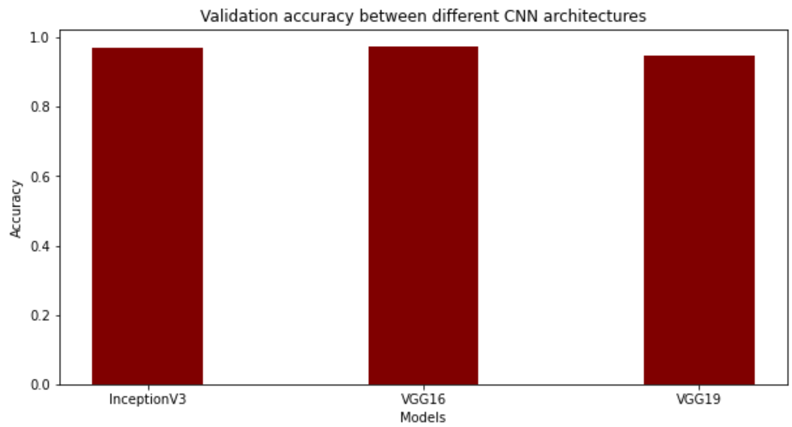

Figure 6.8: Validation Accuracy Between Different CNN Architectures

This graph shows the validation accuracy of all the architectures. These are the ultimate validation accuracy after the final epoch. We can see the comparison of validation accuracy of VGG19, VGG16, and InceptionV3 look side by side. We made the bar graph by taking the best validation accuracy of the last epoch and making it into a line. In the graph, we can see that in the final epoch, VGG19 gives an accuracy of 94%, VGG16 gives an accuracy of 97%, and Inception V3 gives an epoch accuracy of 96%. So, we can say that VGG16 performed best in this scenario.

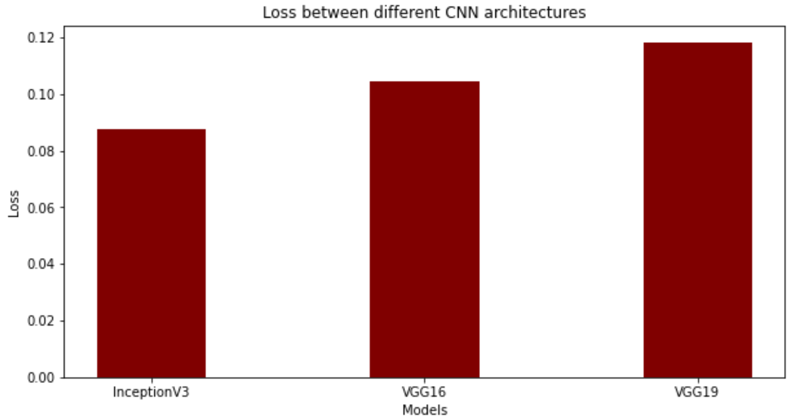

Figure 6.9: Loss Between Different CNN Architectures

All the architectures are shown in this graph, which shows how much they have lost value. After each epoch, the loss function is less. We can see how the loss of VGG19, VGG16, and InceptionV3 look next to each other. This way, we can see how they all compare. Graph It was made by taking the least loss value from the last epoch. In the graph, we can see that in the last epoch, VGG19 gives a loss of 11%, VGG16 gives a loss of 10%, and InceptionV3 gives a loss of 8%. The InceptionV3 architecture gives the least loss value. As we know, the lesser the error in the dataset, the better the testing accuracy. So, InceptionV3 had the best accuracy and the lowest value for the loss function.

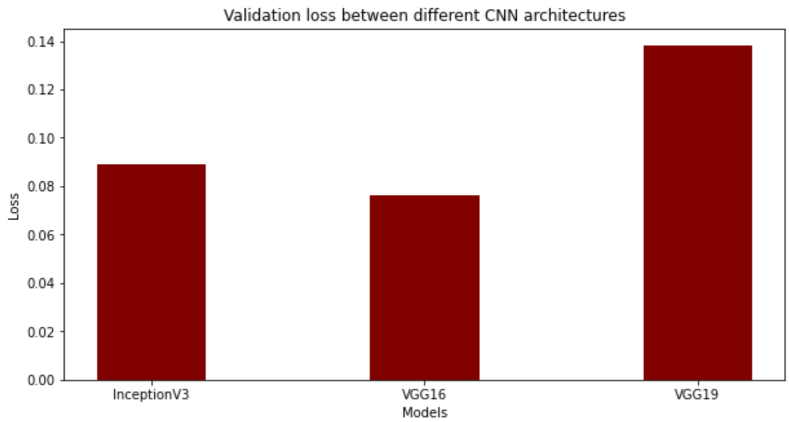

Figure 6.10: Validation Loss Between Different CNN Architectures

We can see all of our models performing better in accuracy and validation accuracy which means our model is generalizing well. As we already find out the accuracy and results of the models, we implemented them in one device as one local server. We achieved a higher accuracy of 96% in VGG16 compared to VGG19 and InceptionV3. We have worked with the 2D slice of fMRI data for achieving this accuracy.

Now we have trained our dataset with this model in a federated setting. With these models, we split the dataset into five clients and performed the training as a decentralized local server which is the main concept of federated learning. From each server we trained the gradients with the models we have found for better accuracy after that, each local server has sent the gradients to the central server, creating transactions for every communication round. In addition, we have used our augmented data for federated training as well. We can see from Table 6.1 that VGG19 showed better performance after testing the global model. As it has more layers it showed more accuracy and better performance compared to other models. After performing training with augmented data, we saw VGG16 now performing better in Table 6.2. But InceptionV3 model still showed poor performance so for getting better results in this model we need more datasets.

Model	Accuracy	Precision	Recall	F1
VGG16	75	0.88	0.52	0.76
VGG19	95	0.94	0.94	0.95
InceptionV3	43	0.52	0.51	0.43

Table 6.1: *Accuracy Between Different CNN Architectures In A Federated Setting With Less Data*

Model	Accuracy	Precision	Recall	F1
VGG16	96	0.97	0.97	0.97
VGG19	97	0.97	0.97	0.97
InceptionV3	62	0.62	0.62	0.62

Table 6.2: *Accuracy Between Different CNN Architectures In A Federated Setting With Augmented Data*

Additionally, we have created the confusion matrices for these models. Using a table called a confusion matrix. It describes the classification model's performance. The rows are the actual classes, whereas the columns are the expected classes. Figure 6.11, 6.12 & 6.13 shows the confusion matrix for VGG16, 19 & InceptionV3 on the dataset. Figure 6.14 , 6.15 & 6.16 shows the confusion matrix for VGG16, 19 & InceptionV3 on the augmented dataset.

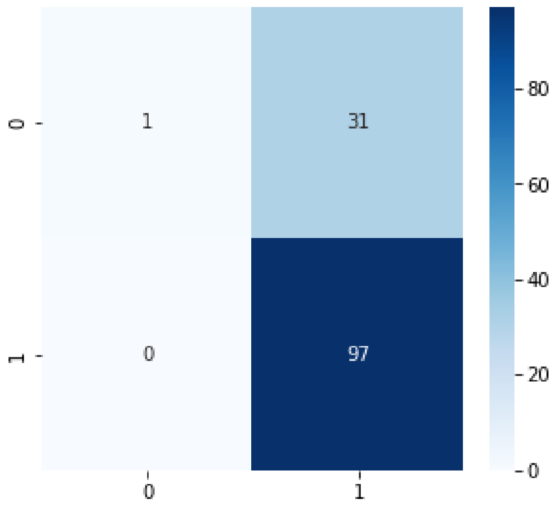

Figure 6.11: Confusion Matrix of VGG16

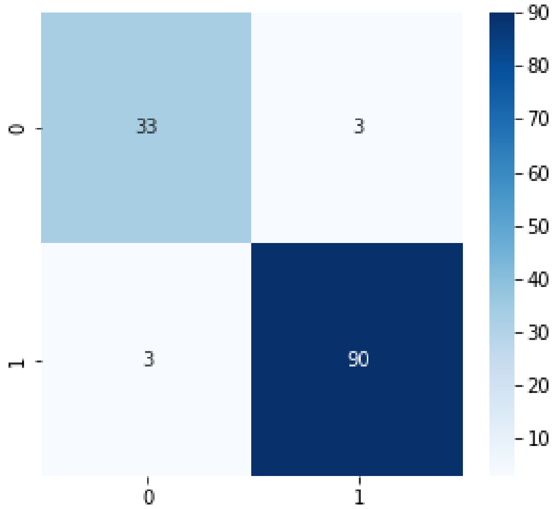

Figure 6.12: Confusion Matrix of VGG19

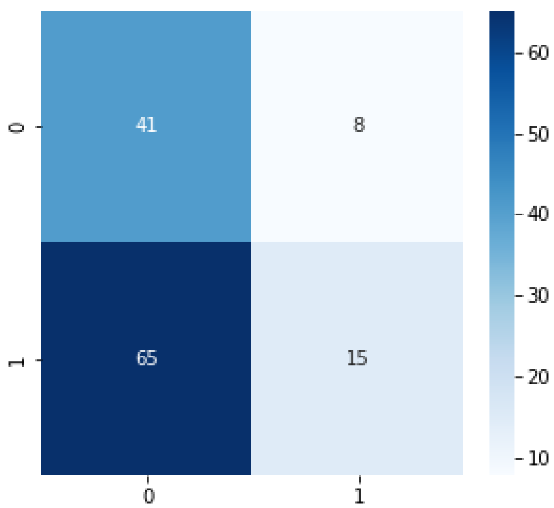

Figure 6.13: Confusion Matrix of InceptionV3

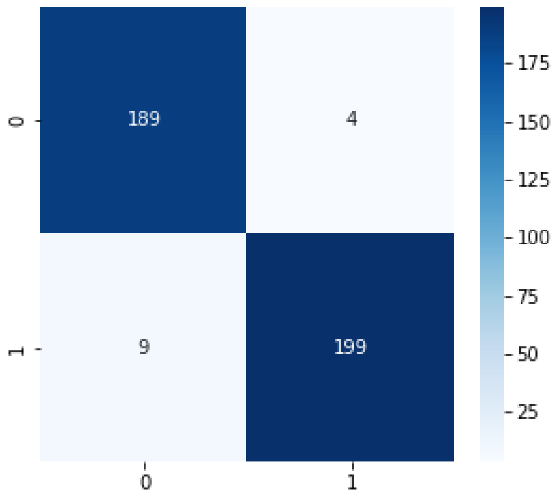

Figure 6.14: Confusion Matrix of VGG16

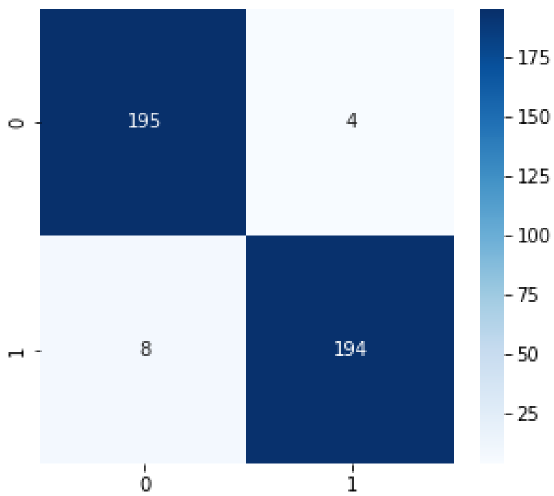

Figure 6.15: Confusion Matrix of VGG19

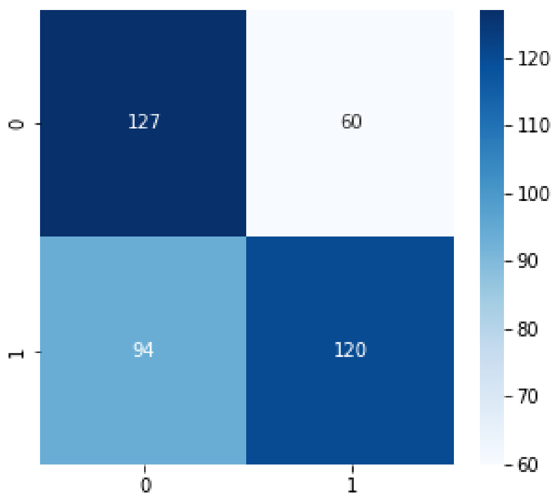

Figure 6.16: Confusion Matrix of InceptionV3

For our Federated Learning technique, each local model was trained multiple times on the complete data set, tweaking parameters as required, which often involved changing data pre-processing functions, and learning rates, and adding layers to suit the models' complexity. To reduce the exorbitant expense of acquiring thousands of training photographs, image augmentation was devised to synthesis training data from an existing dataset. Following that, each global model was created using the local models. We have trained each model for 10 federated rounds. The findings suggest that when training on our dataset for federated settings, it can be beneficial only with the VGG19 model because the more layers it performed higher the accuracy. Also, it performed better with lesser data. So, we can say, for decentralized classification, the VGG19 model outperforms the VGG16 model and InceptionV3. The results demonstrate that the VGG19 model can perform better with only 1290 image samples. After image data augmentation we increased our dataset to 4002 image samples and 2001 image samples for each class. Only then VGG16 model showed better accuracy. For getting better accuracy in the InceptionV3 model we need a far larger dataset. This result proves that VGG19 is the most superior model for detecting Parkinson's disease from Brain images if the dataset is limited.

```
comm_round: 8 | global_acc: 96.758% | global_loss: 0.3507741093635559
3680
23/23 [==============================] - 1s 55ms/step - loss: 0.0680 - categorical_accuracy: 0.9819
comm_round: 8 | global_acc: 95.761% | global_loss: 0.35600757598876953
3680
23/23 [==============================] - 1s 55ms/step - loss: 0.1161 - categorical_accuracy: 0.9597
comm_round: 8 | global_acc: 95.262% | global_loss: 0.36432191729545593
3680
23/23 [==============================] - 1s 55ms/step - loss: 0.0762 - categorical_accuracy: 0.9750
comm_round: 8 | global_acc: 96.010% | global_loss: 0.35596632957458496
3680
23/23 [==============================] - 1s 55ms/step - loss: 0.0699 - categorical_accuracy: 0.9750
comm_round: 8 | global_acc: 97.257% | global_loss: 0.3454716205596924
3680
comm_round: 8 | global_acc: 96.259% | global_loss: 0.3488655686378479
23/23 [==============================] - 1s 55ms/step - loss: 0.0629 - categorical_accuracy: 0.9708
comm_round: 9 | global_acc: 95.761% | global_loss: 0.35581883788108826
3680
23/23 [==============================] - 1s 55ms/step - loss: 0.0604 - categorical_accuracy: 0.9764
comm_round: 9 | global_acc: 96.509% | global_loss: 0.3510851263999939
3680
23/23 [==============================] - 1s 55ms/step - loss: 0.0716 - categorical_accuracy: 0.9750
comm_round: 9 | global_acc: 96.010% | global_loss: 0.3519273102283478
3680
23/23 [==============================] - 1s 55ms/step - loss: 0.0615 - categorical_accuracy: 0.9778
comm_round: 9 | global_acc: 96.010% | global_loss: 0.36047670245170593
3680
23/23 [==============================] - 1s 56ms/step - loss: 0.0552 - categorical_accuracy: 0.9847
comm_round: 9 | global_acc: 95.511% | global_loss: 0.3604992926120758
3680
comm_round: 9 | global_acc: 97.007% | global_loss: 0.3450266718864441
```

Figure 6.17: Global Model Accuracy

Chapter 7

Conclusion

The primary objective of this research is to develop a brand-new framework that protects users' privacy and has the potential to bring about a paradigm shift in the area of distributed machine learning as well as the field of healthcare. The fact that medical professionals have a difficult time diagnosing Parkinson's disease in its early stages is the key motivation for the launch of this project. This is because patients' medical histories are often kept confidential. With this Blockchain based Federated Learning model, doctors can accurately read, discern and provide necessary classifications based on patient data while maintaining its utmost secrecy and safety. We successfully achieved the detection of PD with 95%,96% & 96% accuracy using CNN deep learning architectures which are VGG19, VGG16 & InceptionV3 through centralized machine learning settings. In terms of Decentralized machine learning settings or Federated learning settings, we successfully achieved the detection of PD with 97%, 96% and 62% on VGG19, VGG16 & InceptionV3 by securing privacy. Both traditional machine learning and Federated learning way, all the CNN DL models was trained and tested on a large number of images. On federated settings, we achieved success with sensitivity and accuracy with VGG19 and VGG16. However, the effectiveness of such a model is influenced by a variety of factors, including data and parameter quality. In order to enhance models through communication loops, dataset providers should update their databases as soon as new data becomes available. If all of these factors are maintained, such a design can achieve a level of accuracy that is comparable to or greater than what we demonstrated. Real-world implementation of this model is greatly simplified by the use of image processing and neural network separately; this approach uses extraordinarily little processing resources in decentralized way and is extremely accurate for eradicating the privacy issues which makes this framework much faster and efficient and far better than traditional ml. By adding Blockchains proof of work method in federated settings, this research opens the door of concrete scalability about eradicating all security issues also protecting the data storage and monetary incentives. In terms of discretion, security and authenticability, this proposed model is beneficial for every sector not only limited to healthcare but also insurance, supply chain management, banking, iot, real estate also cybersecurity. Finally, The deployment and assessment of Blockchain-based federated learning have demonstrated its viability and efficacy.

7.1 Future Work

The results we achieved via the use of federated learning approaches may be used to a wide range of real-world situations thanks to our model's alternative approach to the problem of recognizing PD. Using this study, we can see that the network designs used for federated learning are quite precise. These results are not a goal in themselves; because federated learning is way better than traditional ml in terms of privacy preserving way but it's not always assured that much safety sometimes it's also had some breakdown of security for that blockchain needs to be added for reducing the security issues of FL. Additionally, we wish to thank the help we obtained from many Internet sites, especially related research.

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