Comparison of Different CNN Architectures for Brain Tumor Detection using fMRI

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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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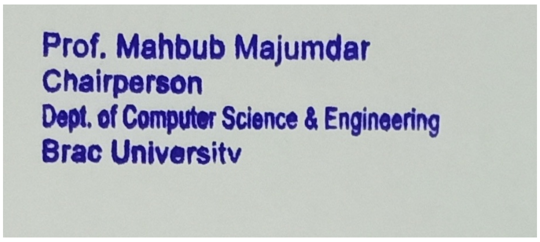

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Abstract

Brain is the most vital organ of human body which controls the entire nervous system of human body. In that case, if anything goes wrong inside our brain the entire nervous system gets collapsed. The brain tumors are the most severe and harmful disease, resulting in a very short life expectancy of the affected patient. Thus, ensuring proper treatment at the early stage is the way to provide the quality of life of patients. Detection of brain tumor is a challenging task in the early stages but with the help of modern technology and machine learning algorithms, it has become a matter of great interest. While detecting brain tumor of an affected person we are considering the fMRI data of patient. Our task is to identify whether the tumor is present in patient's brain or not. Our machine learning algorithm will be convolutional neural network(CNN) that is good enough to generate higher accuracy. We have used some deeper architecture design VGG16 and VGG19 for the better accuracy and comparison purpose. We have done three kinds of classification with these architectures, they are binary classification, five Class Brain Lobe Classification,4 position classification. These different architectures will produce different accuracy level through CNN. Different architectures with different classification will help to find that which one of them meets up the best accuracy level.

Keywords: CNN; fMRI; tumor; machine learning; deeper architecture; classification

Dedication

We would like to dedicate our thesis to Almighty Allah, our parents and teachers for their undeserved kindness and affections.

Acknowledgement

Firstly, all praise to the Great Allah for whom our thesis have been completed without any major interruption.
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Nomenclature

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

ANN Artificial Neural Networks

$BOLD$ Blood Oxygen Level Dependent

CNN Convolutional Neural Networks

DBM Deep Boltzmann Machine

$DICI$ Discriminability Index-based Component Identification

DL Deep learning

DWT Discrete wavelet transform

FCM Fuzzy C-Means

$fMRI$ functional Magnetic Resonance Imaging

ICA Independent component analysis

KNN k-nearest neighbors

LDA Linear Discriminant Analysis

ML Machine learning

MLP Multi layer perceptron

MRI Magnetic resonance imaging

$NGTDM$ Neighborhood gray tone difference matrix

NN Neural Networks

PCA Principal component analysis

RBM Restricted Boltzmann Machine

$ReLU$ Rectified linear unit

RF Random forest

RL Reinforcement learning

RNN Recurrent Neural Network

ROI Region of Interest

SMO Sequential Minimal Optimization

SVM Support Vector Machine

TNC Total number of components

Chapter 1

Introduction

The primary reason of our work was done to find a finer way to detect the brain tumor more accurately. Brain tumor detection is one of the most critical part in tumor treatment planning. Brain tumor can be classified as two types, primary and secondary. A brain tumor of the primary type is not cancerous, which is called benign tumor. A malignant tumor is of the second type which stores cancerous cells. A malignant tumor is very dangerous as it can take away the life of a person. Therefore, this work was done to find out if there is tumor in the brain or not.
The introduction reveals a small overview of the whole work. Firstly, the motivation part comes. The motivation part is there to shows the reason of our work. The reason of our choosing this topic and the importance of this subject was described in the motivation. Later come the thesis overview. The thesis overview gives an overall encapsulation of the whole thesis work. It is there to show some of the ideas of the important topics and the outline of the whole working process. The thesis overview gives a small description of the work as well. Lastly, the thesis orientation is the part where the orientation of the paper is shown. It describes the consecutive chapters and which chapter contains what kind of information.

1.1 Motivation

Brain is by far one of the most important organs of the human body and tumor is the unusual growth of the tissues. A brain tumor is an unnecessary cell growing in the brain or central spine canal. It is an unrestrained progress of cancer cells in any portion of the body. Tumors are of different forms and have different features and different treatments. The most dangerous tumor is a brain tumor where the tumor is in the brain and very difficult to cure it. Even though there are healthy cells, the unhealthy ones can attack them. Being a vital organ, any problem in the brain effects the whole body. The senses that are used to do the regular human works can also malfunction due to any problems in the brain. Same goes for the other parts of the body as well.

The primary reason of our work was done to find a finer way to detect the brain tumor more accurately. Brain tumor detection is one of the most critical part in tumor treatment planning. Brain tumor can be classified as two types, primary and secondary. A brain tumor of the primary type is not cancerous, which is called benign tumor. A malignant tumor is of the second type which stores cancerous cells.

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This paper aims to detect brain tumors using data from fMRI (function magnetic resonance imaging) to identify the effected brain cells. After reading various research paper we understood that detection of tumor is the prime target of the curing process. Thus, we decided to work on this subject so that we can compare some of the different architectures of CNN to observe the better model to find the accuracy. Moreover, we also tried three different set of classifications to see what type or data produces the better accuracy among these. In future we would like to work more on this project of ours and we will try our level best to find a better, cheaper and easier process to detect brain tumor.

1.2 Thesis Overview

The field of medical diagnosis is a huge one and medical image data is very a vital part of it. For medical diagnosis, we need to take the medical image information. Mostly used images are CT scan, X-ray, and MRI etc. To obtain the internal structure of the brain, Brain Scan is used. For its high resolution, MRI is the most used brain scan technique. MRI has a lot of information about the structure of the brain and shows any abnormalities within the brain cell [70]. There are many advanced methods in Machine Learning and Deep Learning which are used for image processing. In comparison, Neural Networks (NN) and Support Vector Machine (SVM) are the approaches widely used in recent years for their successful implementation [55].
The main goal of Functional magnetic resonance imaging or functional MRI (fMRI) is to detect the changes of blood flow and measure brain activity [48]. This technique is based on providing cerebral blood flow coupled with neuronal activation. When a brain area is in use it also increases blood flow to that region [36]. This paper primary target is to find out brain tumors using FMRI (magnetic resonance function imaging) data to assess brain activity by detecting changes in blood flow.
When it comes to spot a brain tumor, BOLD fMRI (blood oxygen level-dependent functional magnetic resonance imaging) is a very widely used and well-established method for determining the locations of eloquent cortices, such as primary motor cortex (PMC) [13]. Since this technology was developed in the early 1990s, it has been applied extensively to the study of brain function in both healthy individuals and brain tumor patients [36]. However, to find a better understanding of brain dynamics, a proper model is required to trace this information and the mental processes that creates it. . One of the important clinical applications for BOLD fMRI is in presurgical mapping, where trying to identify any of the eloquent cortices can guide the planning and the actual resection of the tumor [15].The ability to generate accurate functional maps using BOLD fMRI signal is not easy. It is critical for optimizing the surgical resection strategy which, in turn, can assure maximum preservation of function [9][11].
Machine learning is a very common technique to figure out the details in fMRI images. Recently, in the fields of machine learning as well as data mining, deep learning has gained much attention [29], and it has been proven that deep learning approach is splendid in learning high-level and mid-level raw data features [37]. Generally, a deep learning architecture comprises of deep network layers by stacking

several related building blocks. The bottom layer collects input and then passes the transformed input versions toward the next layer, all the way up to the top layer. As a result, a deep learning model's architecture performs as a whole as a hierarchical feature extractor.. Over the past few years, there have been that literature entities that have implemented deep learning models in fMRI data modeling and related applications, for example [35]] using DBN (Deep Belief Network) to learn physiologically relevant representations from fMRI data [49] integrating DAE (Deep Auto-Encoder) with HMM (Hidden Markov Model) for investigating the functional connectivities in resting-state fMRI [46] used the RBM (Restricted Boltzmann Machine) to mine the latent sources in task fMRI data and [59] CNNs (Convolutionary Neural Network) are used to identify functional brain networks derived from the fMRI.

Of all the deep learning models available, one of the most common methods is the CNN [34]. It is influenced by the visual system of humans are similar to classical neural networks. This architecture is specially built on the basis of the explicit assumption that raw data are two-dimensional (images) enabling us to encode such properties and also to decrease the number of hyper parameters. The topology of CNN uses spatial relationships to minimize the number of parameters that need to be learned, thereby enhancing general training for feed-forward back propagation.

One of the most used ways of processing images in python is through numpy arrays. We have loaded our image through nibabel. Then needed data was collected from the images and then cast it in a numpy array. Overall, NII babel library has been used to convert the 3D images to 2D images. Because 3D images are not suitable for applying neural network.

Then the method of normalization is applied on 2D images, which splits each image into several slices and these slices indicate brain's axial states. Normalization is usually the process of arranging a database to eliminate complexity and increase consistency of the data. It is a significant part of the design of relational databases, as it deals with the performance, speed and accuracy [41]. When it comes to training a deep learning neural network, Batch normalization is a popular method. This method helps to normalize the hidden unit's activation values to ensure the distribution remains the same while training [64]. Hidden unit's activation may slow the process of the training. The thought of batch normalization came to mind and was designed to solve the disturbance of internal covariate shift. Research shows that training neural network can be done much accurately if input data are normalized or whitened [10].The figure showed in Figure 1.1 is normalization process.

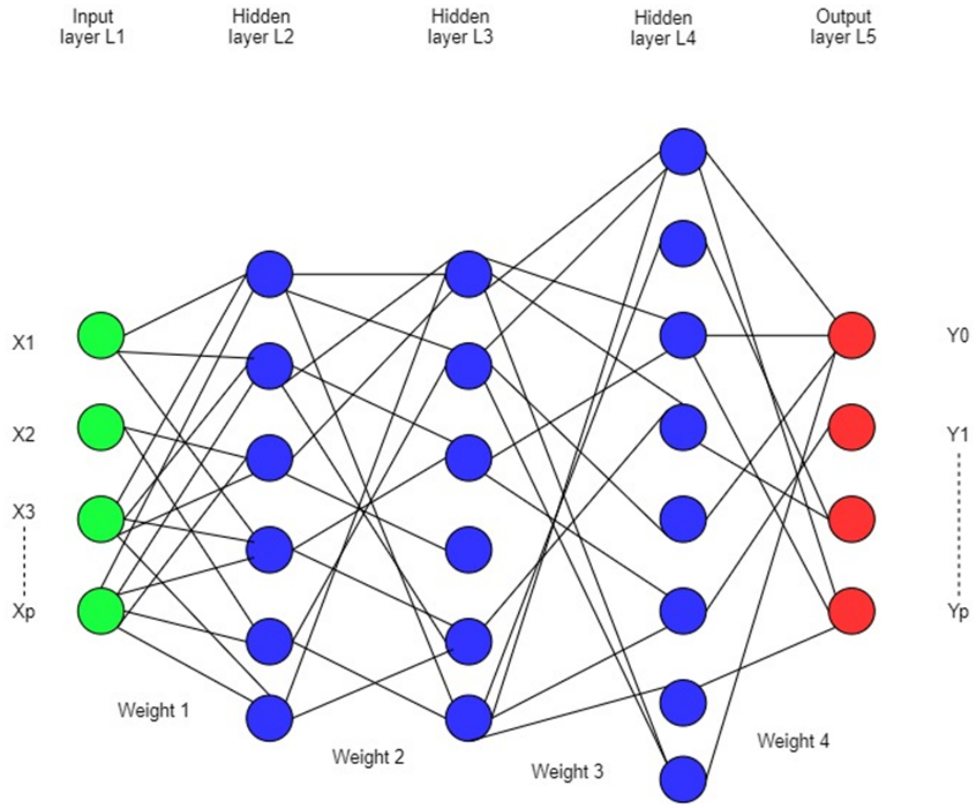

Figure 1.1: Normalization

We have a deep neural network here with 3 hidden layers including an input and an output layer. As shown in the Figure 1.1, each hidden layer does have its own weight matrix and bias vectors. Using the weight matrix and bias vector the input at each layer goes through some transformation. After that, the pictures were augmented. Deep learning networks uses a huge amounts of data to function properly. However, for many datasets, especially historical documents, the data is fixed, so augmentation must be performed by modifying the original data. Sometimes, the dataset needs more data for given dataset if it is not big enough. For image recognition, augmentation is applied using simple transformations such as flipping images horizontally, scaling, or sampling sub-windows of the images [32]. Some of the basic data augmentation techniques are:

1. Flip: The horizontal and vertical axis are flipped.

2. Rotation: Certain degree of rotating an image.

3. Crop: A section or portion of the given image is cropped or resized.

4. Add Noise: Gaussian noise is added to the selected image.

5. Colo Jittering: Random color manipulation [83].

Later on, the data set was introduced to NN (Neural Network). NN corresponds to neuron structures, whether of an actual or artificial origin. Neural networks have a tremendous capability to collect useful data from imprecise data, which is used to identify trends and to identify patterns that seem to be hard to understand for machine or human being [25]. In the beginning, large amounts of data are

fed to the NN. Generally, training is given by providing the input and informing the network about what will be the output [20]. A CNN is a type of deep neural network which is occasionally used on image type data or any kind of complex classification. Convolution, Max Pooling, Dense and Dropout are some of the layers of the architecture of the CNN [47].
The evaluation of our dataset was determined by a set of 20 images. After applying all the factors stated above, the entire dataset was divided used for 3 types of classifications. The first type of classification was binary classification. The binary classification was used to determine if the brain has any brain tumor or not.Two directories were created named Train and Test. The train directory was used to train the model. However, the test directory was created to test the accuracy of the trained model. Both the Train and Test directory had 2 types of internal directory. Those two directories were made with brain tumor effected images and non-effected images. The second type of classification was done to check the brain tumor of the brain according to the lobes of the brain. This has been named 5 class classification which used the 4 region of brain. The train and test directories were also divided according to the 4 lobes of brain: the frontal lobe, the parietal lobe, the occipital lobe.. And there is another directory where there are the images of the non-effected images. The third classification was done to find the pattern of which side of the brain has tumors more often as they were done according to the 2D Cartesian coordinate system. The Train and Test directory were divided again. However, this time it was based on the position of the tumor according to the axis they are in. The four directories inside train and test has images of the four different position based of axis: Front Right, Front Left, Bottom Right, Bottom Left.
There are many widely used data set of the CNN architecture. However, in our work we used three of those. The architectures are VGG16, VGG19 and InceptionV3. The main goal of the VGG architectures are to show classification or localization accuracy. The VGG16 and VGG19 have same 16 convolutional layers. However, VGG19 has 3 extra layers which are fully connected to each other [69]. The inception v3 is a CNN architecture which is trained from ImageNet database. The training was done and to complete it one million images had to be used [54]. At last, these three architectures were used to figure out the accuracy of the data set of three different classifications.

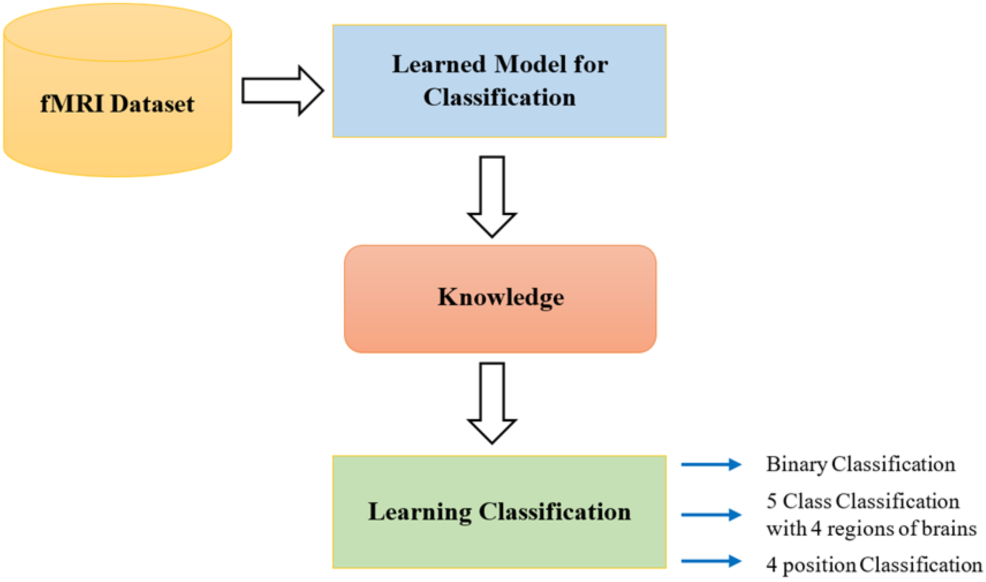

Figure 1.2: Brain tumor detection by deep learning

Figure 1.2 shows a short description of the process of our work. Our work is a different sort of work due to its type. It is a work which is kind of a survey on the use of different architectures of CNN. The main purpose of the work was to show how the architectures work on differently classified data and different models.

1.3 Thesis Orientation

The subsequent sections of the paper have been organized in the following manner. Chapter 2 includes the related work and existing approaches which comes close to our work. The past work on related or co-related subjects have been the focus of this chapter. Chapter 3 analyzed the background study of this subject as comprehensively as possible. Chapter 4 introduces the dataset, the way of data processing for this paper, as well as the proposed approach for finding accuracy of the model. Chapter 5 provides the experimental results as well as the related discussions. Finally, in Chapter 6, the conclusion and the summarization of the report was included.

Chapter 2

Literature Review

MRI is a versatile imaging approach to generate images of the organs of our body. MRI became a very famous and widely used imaging brain technique in a short time as it can scans illustrate more clearly, can detect difference between healthy and diseased tissue and can provide more information about organs [92] . A technique that emphasis on the resonance brain image classification that was addressed by researchers named named Javed et al. [30] using perceptual texture features, fuzzy weighting and supporting vector machine. Their main purpose was to do to classification of brain tumor image into two different class are as classified brain image help to provide correct treatment. They classified the magnetic resonance image into normal and abnormal classes using the SVM algorithm. They extracted feature based on textural features and invariant moments [31] which is an image characteristic remain unchanged under the action of a transformation group. Invariant moments incorporate with invariance to scaling, rotation, and translation [1] . Researcher assigned different real number weights for extracting features according to their discrimination capability using Fuzzy logic to increase classification accuracy. Extracting seven invariant moments, some measurement such as coarseness, contrast, busyness applied in their research. For computing Textural features, they used neighborhood gray tone difference matrix (NGTDM) that provide a difference among Normal, glioma, sarcoma, meningioma classes of MRI brain images. They found that normal image had the maximum value for first moment and sarcoma, abnormal, glioma had the second, third, fourth maximum values respectively. At the stage of seven moments, sarcoma archives the lowest value. However, classification of abnormal brain is relatively hard and challenging problem too. The proposed system is confirmed utilizing the Harvard medical brain database, which comprises MRI T2-weighted pictures (of 256256 spatial resolution). Database contains 48 normal brain images and 25 brain images for each disease. The proposed techniques produce less variance in results as the orientation and scale changes, SVM algorithms gives better classification accuracy. In SVM based classification, when the accuracy rate is high, they observed that the computation time accuracy rate is low. In their research, they used SVM for classify the brain images into two class, and we performed three types of classification using three types of deeper architecture of CNN for comparing the accuracy for detect which one archives the best accuracy level.

J. Seetha et al [74] proposed a system that is automatic brain tumor detection to ameliorate the accuracy as well as as to diminishing the computation time by using CNN classification algorithm. Authors collected dataset from different online sites. They used five-layer convolutional neural network as image in CNN can be scalable and can take 3d input and output volume. They divided the image into two different directory and categories as tumor and non-tumor image. Preprocessing, feature exaction and classification performed in the training stage, image resized come off in the preprocessing label and trained last layer which is fully connected layer in python implantation as a result, they acquired the high performance with least time. They applied gradient descent algorithm for calculating loss function to improve the testing accuracy. Researcher achieved the highest probability score value on tumor brain category and lowest probability score value on non-tumor brain category. The performance of that proposed technique is compared with the persisting schemes such as SVM. After calculating accuracy depends on classification output result and feature extractions value, researcher noticed that CNN is the efficient automatic brain tumor detection techniques and it archives 97.5% testing accuracy with low complexity compared to exist technique's accuracy. Nevertheless, they disregarded to show comparison between different types of deeper architecture of CNN.

At the earlier period, experts or doctors used to do manual segmentation which was so much time consuming and very tough. Nowadays automatic Brain tumor segmentation became a vital process in medical science for reducing difficulties in segmentation [77].As we know automatic segmentation helps to detect the brain tumor in the early stage and improves the treatment system.Y. Pan et al [42] conducted research on Brain Tumor detection and segmentation. Authors used machine learning algorithms named NN and three-layer CNN considering MRI images limitation on shape and size of brain tumor that varies one patient to other patients. The aftereffects of Multimodal Brain Tumor Image Segmentation Benchmark (BRATS), composed mutually with the MICCAI 2012 and 2013 meetings, show that quantitative evaluations revealed critical inconsistency between the human raters in dividing distinctive tumor sub-districts and the Dice Scores was ranged from 74% to 85% . Huang et al. [33] use an innovative method in processing features to achieve accuracy of 74.75% in tumor segmentation on the mean Overlapped Volume using subspace feature mapping. For grading brain tumor, input data cleaning, data selection, sensitivity and specificity classification taken place. On their research they found a same result while using one layer and final layer structure of CNN with different kernels. They proved that Deep learning algorithm with more layers does not require to obtain better performance. Researchers checked out 213 patients' image samples for training from BRATS 2014, they picked up 195 patient's data, explored that 170 are high-labeled and 25 low-grade patients' data. The outcomes show the greatest improvement of 18% on reviewing execution of CNN dependent on affectability and particularity contrasted with baseline NN. However, authors show a comparison between between baseline NN and CNN only rather than comparing accuracy of different CNN architecture model.

Hanwat et al.[85] research on "Convolutional Neural Network for Brain Tumor Analysis Using MRI Images", proposed a CNN based brain tumor classification method. They proposed six step consisting methods. Methods are input image, image preprocessing, image segmentation, feature extraction, classification and performance evaluation. Authors used CNN, Random forest (RF) and K Nearest Neighbors (KNN) classification techniques for classify the brain tumor MRI images. They worked on 94 MRI images. They perform Inception V3 architecture of CNN consists of four layers such as convolutions, pooling, max pooling, and fully connected layers. Random forest classifier was adopting to make a group of many decision trees and each decision tree produced one result. Later on, their experiments compared with others popular machine learning classifier like CNN achieved 80% of accuracy and K-Nearest Neighbors achieved 74% of accuracy, they analyzed that CNN is considered as perhaps the best classifier, and it's work better than others algorithm. Research showed that the normal exactness of the brain tumor characterization with the assistance of Convolutional Neural Network classifier is 98% with cross-entropy is 0.097 and approval precision is 71%. Thus, the Convolutional Neural Network is seen as one of the effective techniques for performing various phases of brain tumor arrangement. Authors were successful to show comparison between CNN, RF, and KNN but failed to show comparison between different architecture of CNN that mainly helps us to find out which of architecture gives more accuracy.

A research paper by Huang et al [67] carries the significance of pre-surgical functional mapping as well as tumor tissue detection are promising imaging techniques and which takes place by Bold rs-fMRI that is less clear and complex. They accept Independent Component Analysis (ICA) to degrade individual rs-fMRI data into multiple elements. Discriminability Index-based Component Identification (DICI) used to identify tumor related components and it was robust. They used optimized subject-specific total number of components (TNCs) for the best output. They took 32 glioma patients from three center as well as 28 patients' data from the fourth center with non-brain musculoskeletal tumors. Authors able to obtain the accuracy rate for the three centers are 100%, 100% and 93.75% for glioma tissue detection, respectively, and 85.19% for musculoskeletal tumor detection.

Brain tumor became a name of fear in disease world. There are discovered over and above 120 known types of brain tumor. Some tumors among them is very dominant, such as meningioma, glioma, and glioblastoma. According to a series called "Brain Tumor Facts Figures" exposed that the average annual mortality rate of brain tumor was 4.33 per 100,000 Americans in between 2010-2014 and analyze that the primary brain, and CNS tumors attribute for an estimated 16,616 deaths. Thus, detecting a brain tumor at an early stage is much more indispensable for giving diagnosis at a beginning stage. Roy et al.[73] has conducted a study of Brain Tumor Classification and Performance Analysis that focused on fast and efficient identification of brain tumor. They divided their dataset in five types. Five types were Type 1 (Sarcoma); Type 2 (Meningioma); Type 3 (Metastatic adenocarcinoma); Type 4 (Metastatic bronchogenic carcinoma); 5 (Glioma). Researchers applied Histogram for calculating mean, variance, skewness, Kurtosis, entrophy. All these parameters used as an input of texture segmentation, normalization, Back propagation algorithm. After normalized the image slice, slice extracted into feature vector which is consists of 12 features and those feature vectors produced around 20 input. They discovered that type 1 contained I1-I4 number slices, type 2 contained I5-I8 number slices, type 3 contained I9-I12 number slices, type 4 contained I13-I16 number slices and type 5 contained I17-I20 number slices. By enforcing MRI, Histogram, artificial neural network fuzzy inference system (ANFIS) [50], researchers are able to obtain 96.34% accuracy from their recharge. Nevertheless, they did not show any comparison between different classifiers and architectures.

Recent research shows that data augmentation is a very important technique in medical image segmentation. Chenget al [39] mainly concentrate on Enhanced Performance of Brain Tumor Classification via Tumor Region Augmentation and Partition. They adopt intensity histogram, gray level co-occurrence matrix (GLCM), and bag-of-words (BoW) model for handling large data set. Then they convert 3D image to 2D image as 3D image have some limitation. Researchers performed ROI segmentation, extract local features, constructs dictionary, represent histogram. After represent each ROI, they perform training work for classifying ROI into different tissue types. They have created a dataset that contains 3064 images slice with meningioma, glioma, and pituitary types brain tumor and stored all the image in three groups named axial, coronal, and sagittal group. Researchers found that using the augmented tumor region as ROI produced more accuracy's compare to assume tumor region as ROI, and it gives 10.92%, 6.57% and 4.65% more accuracy for intensity histogram, GLCM, and BoW model, respectively. Adopting ring partition in augmentation process, they were able to accord 87.54% accuracy in intensity histogram, 89.72%, and 91.28% accuracy in GLCM, and BoW model, respectively. In our binary classification using different architecture of CNN, we get 95.70% - 96.04% accuracy.

Ensuring good performance of the deep learning model becomes more strenuous for large dataset. Therefore, augmentation used for improve the model performance as well as expand the size of train set. There are available so many commonly used augmentation like flip that used to flip image horizontally and vertically; rotation that used rotate image it at right angle and rotate to finer angle; scale that mainly scaled the image in outward or inward; crop; translation that involved move the image along the x or y or both direction. Mok, Tony and Chung, Albert have several studies on Learning Data Augmentation for Brain Tumor Segmentation. Researchers involved automatic data augmentation for reducing time, escape from manual labeling problem and avoiding modalities and imaging protocols [71]. Authors recruited two types of CNN on their experiment that used for generic data augmentation and segmentation work. After performing all the procedures, the researchers track down that comparison result of segmentation performance between baseline GANs, a coarse-to-fine GANs and CB-GANs, and notice that the average value increased by 3.6% each dice. Then they show comparison between proposed model and traditional augmentation model where proposed model performance improved on average by 3.6% per dice. In our study we present a comparative study between the convolutional architectures whereas researchers showed comparison between augmentation result.

Deep learning is a small part of machine learning that largely used in image recognition, speech recognition, visual art processing, Natural language processing, medical sectors, military, etc. Over time, deep learning outspread its demand in every sector in our life as it has the power of enlighten machines intelligent, prevent overfitting problem and improve capacity of computing devices [79]. Researchers have performed several studies on classifying brain tumor using different types of algorithms, architectures, methods. Paul et al.[58] focused on a study of brain tumor classification using CNN which is class of deep learning. In implementation part, they applied feedforward neural network containing convolutional layers and back-propagation learning for assigning weight and bias to the convolutional or fully connected layer. They used Rectified Linear Unit (RELU) activation function and max function to achieve neuron's non-linear activation. Researcher's handled the data processing using pre-processing process. Preprocessing covered by vanilla data preprocessing, tumor location, tumor zoom for passing image input to the neural network, tracking tumor locations, zooming the brain tumor region in scan, respectively. After processing Image augmentation; small or large image size process; rotation, shift and mirror transformation taken from to solve the overfitting problem; constructing network, then they trained their data set. Finally, authors able to make up their level best testing accuracy on the best trained neural network which is only 91.43%. Their research provided testing accuracy is less than compare to our research testing accuracy as well as they did not show any comparison between different architecture of CNN. This was one of the reasons for conduct our research.

Biospy is a process that required a surgery to examine and remove abnormal cells from our body for identifying health conditions. It is an invasive procedure that is not much flexible compared to other tumor classification methods. Therefore, researchers named Badza et al [99] leaded an experiment on brain tumor classification. Their purpose was to classify three types brain tumor using machine learning algorithm like CNN which is simpler, accords better performance than Biospy to avoid brain surgery. Authors have prepared image data set, preprocessed and augment it for training purpose. They have trained network on 3064 images in three planes which were acquired from 233 patients by using an Adam optimizer and shuffling data. Researchers have applied k-fold cross-validation method to test the performance of the system based on average precision, recall, F1-score result. The loss function was scored 15.7% using subject-wise 10-fold cross-validation testing method and scored 3.4% using record-wise 10-fold cross-validation method. They explored that record-wise 10-fold cross-validation method produced better accuracy compare to state-of-the-art methods, and the accuracy was 96.56% for the augmented database.

The k-nearest neighbors (KNN) algorithm is a supervised machine learning algorithm that became very popular for its particular uniqueness such as simple in character and its upstanding performance for small size data set doing classification [62]. Aiwale et al. [80] accepted KNN, LLOYED and OSTU algorithm for detecting brain tumor. Their proposed methodology includes pre-processing, image conversion, wavelets transform, feature extraction and classification. Extracted features named Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness by using wavelet transform. Researchers analyzed that malignant tumor occupied 80% area which tumor has the ability grow up and can affect the others part of the body, and Bennie tumor occupied 45% area in the brain cells. Authors have adopted KNN algorithm that might be face difficulties while handling the large size data set. However, researchers have focused on detecting tumor and its area that is occupied by the abnormal cells of brain rather than compare with others algorithm architecture, calculating its testing accuracy.

Mathematical morphology is a name of method that used for image segmentation. This method perform depends on two tools named watershed transform and homotopy modification. Over time, watershed line became very popular technique in some extend for segmenting image [4]. Beucher, Serge and Lantuéjoul, Christian explored the concept of watersheds line for segmenting bubbles image and scanning electron microscope metallographic pictures [2]. F. MEYER proceed to pragmatic approach after showing overcome method of under segmentation and close broken contours [4]. Devkota et al. [66]. focused on Early Stage Brain Tumor Detection. They used Mathematical morphology technique for segmentation process to improve the computation time. They adopted median filter for performing image pre-processing; mathematical morphology for doing segmentation; principal component analysis (PCA) for executing feature reduction, SVM with GRB kernel for implementing classification. They able to make the accuracy rate 92% in detecting cancer and 86.6% accuracy in classification. Their method had two limitation such as least accuracy rate where our classification produced more accuracy over their accuracy rate and another on is computational cost.

Tonmoy et al. [88] introduced a model based on Fuzzy C-Means clustering algorithm accompanied by traditional classifiers namely SVM, KNN, Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes and RF and CNN. Researcher processed the model through Skull Stripping by Otsu Thresholding and Connected Component Analysis; Filtering and Enhancement; Segmentation using FCM; Morphological Operation; Tumor Contourin; Feature Extaction; Traditional Classifier; stage evaluation. After experimenting the traditional classifiers, they found the highest accuracy by SVM classifiers which is 92.42%. Study showed that CNN provides more accuracy than traditional classifiers.Mohsen et al.[56] also studied on segmentation using Fuzzy C-Means (FCM). They applied Deep Neural Network classifier incorporate with the discrete wavelet transform (DWT) and principal components analysis (PCA) for classifying brain tumor. They used data acquisition, image segmentation, feature extraction and reduction, classification as a methodology. Authors able to make high accuracy rate is 96.97% using DDN classifier compare to others classifiers namely KNN, Linear Discriminant Analysis (LDA) and Sequential Minimal Optimization (SMO) classification methods. However, their research has some limitations such as poor performance record and a high complexity.

CNN has some architecture and ResNet is one of the very faster and efficient architecture of CNN with 152-layer [60]. Liu et al.[91] have adopted ResNet classifier for brain tumor classification for avoiding overfitting problem, reducing number of parameter and improving the classification accuracy. By using ResNet architecture, they accord 95% classification accuracy. Tammina, Srikanth conducted a research on classifying image using pre-trained model VGG-16 architecture of Deep Convolutional Neural Network. A series of layers applied to input image namely convolutional layer, activation function (RELU), pooling layer, fully connected layer. They achieved 72.40% validation accuracy using the basic block neural network, and 95.40% validation accuracy by applying fine-tuning CNN with pre-trained VGG16 model and image augmentation [95]. Srinivas et al. [82] proposed a model for classify brain tumor using Transfer Learning incorporate with Alex net architecture of CNN. Authors adopted two optimizers namely sdgm and adam optimizer. They explored that the model with adam optimizer accord better accuracy than sdgm. The accuracy rate obtain by sdgm optimizer is 96.25% and obtain by adam optimizer is 97.91%. Researchers [91] [95] [82] failed to show comparison between different architecture's testing accuracy as they did only one classification by using the only one architecture of CNN in their research.

Chapter 3

Background Study

We square measure operating to spot brain tumor by magnetic resonance imaging information with the assistance of learning methodology. brain tumor is largely a condition of abnormal tissue growth. Growing tumor will squeeze essential brain components and make severe health issues. Tumors will kill healthy brain cells immediately. Tumors may also injury healthy brain cells indirectly by overcrowding different regions of the brain by making inflammation, swelling of the brain and pressure at intervals the bone[22] . The importance of distinguishing brain tumor is alone as these tumor cells shortens lifetime of individuals than expectancy rate and additionally injury brain cells. Moreover, as brain is that the key organ of body thus once something goes wrong with brain the complete body suffers. As brain send signals to remainder of the organs. Brain tumors will have an effect on thinking talent, injury memory cells, expertise learning difficulties, face fatigue and on. From a hunt we have a tendency to came to grasp that just about twenty eighth individuals suffer from vision downside thanks to neoplasm[72]. So as facilitate to assist individuals to urge eliminate these issues we've got go with our planned model that may help to find tumor victimization completely different architectures. By victimization (different totally completely different completely different) architectures mean different quite accuracy level in results. In fact, the architectures can manufacture a comparison among all the opposite architectures that we've got used to this point for our planned model. These architectures can propagate with CNN rule. CNN could be a technique in DL that feeds artificial neural networks applied to visual pictures [45]. The most feature of CNNs is learning capabilities and providing unlimited accuracy instead of ancient machine learning and neural networks which may be achieved by increasing samples of coaching and thus ensuing to an additional strong and correct model [48],[68]. CNN works higher for MRI processing [14]. Additionally, MRI could be a powerful and effective non-invasive tool in brain operate study [43]. MRI information is sweet in terms of image extraction of brain tumors and CNN is powerful enough to supply higher level of accuracy. A CNN could be a special kind of multi-layer neural networks designed to directly acknowledge visual patterns from component pictures with pre-processing [94]. The term ''Neural Convolutionary Network" reflects that the network employs a mathematical methodology referred to as convolution.

3.1 Human Brain

The brain is one of the enormous and most intricate organs in the human body [97]. The weight of an adult's brain is nearly 1.0 kg-1.5 kg which is nearly 3 lbs. It consists mainly of neurons-the core unit of the brain and nervous system [8]. Brain gives us consciousness about ourselves and also about the environment where we live. There are almost 100 billion neurons in human brain. Some of the most basic features of brain are storing sensory information, controlling blood pressure and respiratory system and hormone releases [84]. Brain is composed of three major components they are brain Stem, cerebrum, cerebellum. The Brain stem consists of a combination of grey and white matter that is called reticular formation. It connects the spinal cord with the cerebrum and cerebellum. According to the Mayfield Clinic, the main part of the human brain is the cerebrum that is separated into two hemispheres. Cerebrum is the main portion of the brain that includes both the right and the left hemispheres. The hemispheres are bound to a collection of fibers called the corpus callosum, that transmits information from one hand to another [19]. Each hemisphere controls the body's opposite side [57]. Cerebellum is hemispherical in shape. The brainstem lies down, and the cerebellum sits behind it (Figure 3.1) [38]. There is cerebral cortex in human brain, which is the outermost layer, consisting of four lobes: the frontal, parietal, temporal and occipital lobes [3] (lobes are showed in the Figure 3.1).

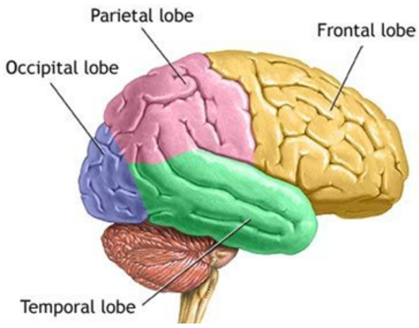

Figure 3.1: Basic structure of a Human Brain

3.2 Brain Tumor

Tumor is basically a condition of abnormal tissue growth. Growing tumor can squeeze essential brain parts and create severe health problems [57]. Tumors can kill healthy brain cells straight away. There are plenty of different types of brain tumors. Some brain tumors are noncancerous and cancerous. Despite decades of study, brain tumors remain among the most lethal of all cancer types. The ability of these tumors to withstand nearly all traditional and novel therapies is partly due to the special cell-intrinsic and micro-environmental properties of neural tissue [26], [81]. If the tumor cells are not detected at early stage it may hamper the patient.A picture with brain tumor is showed in Figure 3.2 there are some symptoms of brain tumor they are given below.

1. Headaches: Headaches can be serious and deteriorate with movement or early in the morning

2. Myclonic: Due to myclonic Single or multiple twitches, muscle jerks, cramps tales place.

3. Tonic-Clonic (Grand Mal): There can be loss of consciousness and body sound, accompanied by muscles that twitch and relax, which is called contractions. It can also regulate to loss of body function regulation, that can be failure of the bladder control.

4. Sensory: It can bring changes in sensation, vision, smell, and/or hearing without losing consciousness.

5. Complex partial: It may cause a loss of consciousness or partial or complete loss of Consciousness, repeated, involuntary movements such as twitching.

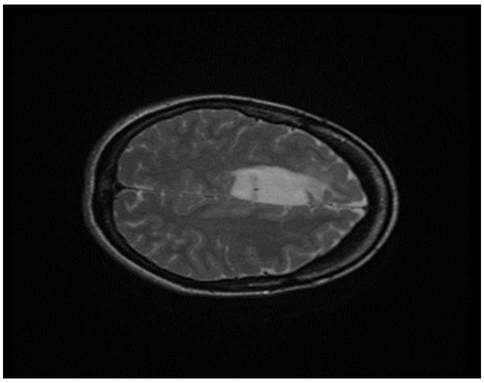

Figure 3.2: fMRI Image of a Brain having Tumor

3.3 Machine Learning

Machine learning is associate degree application of computing (AI) that offers systems the power to mechanically learn and rest on expertise while not being specifically programmed. Machine learning focuses on the programs being created that may access information and use it to be told for themselves.

The learning cycle starts with observations or information, like instances, direct expertise or feedback, so as to go looking for information trends and create higher choices within the future, based. The primary objective is to permit laptop to be told mechanically while not human interference or help and to vary their actions consequently [93].

The external setting may be a set of external info, delineated in some type, that may be a supply of external info. Training is that the technique of translating external info into information.

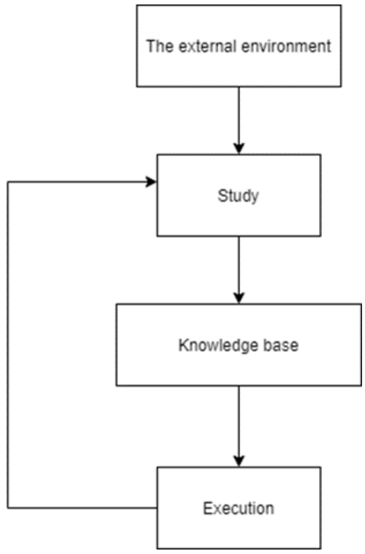

Figure 3.3: Basic Machine Learning Model

In the Figure 3.3, first, external info is gathered from the environment; then info is regenerate into information and information is placed into the mental object.The basic ideas of application square measure contained within the mental object.The execution relation is that the method of mistreatment information within the mental object to complete a specific task, and it feeds back some info that has been noninheritable in the process of finishing the task to guide any analysis [76].

There are 3 type of approach machine learning:

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

3.3.1 Supervised Learning

From Figure 3.4, essentially, this method teaches machines by example. Systems are exposed to significant quantities of classified data during preparation for supervised learning. The word "supervised" learning is derived from the fact that this type of algorithm training is like having a teacher oversee the entire operation. Training data will consist of inputs coupled with the right outputs when a supervised learning algorithm is equipped. The algorithm scans the data for patterns that correspond to the desired outputs during training. After training, a supervised learning algorithm will take on new unknown inputs and determine which mark should be used to classify new inputs on the basis of prior training results [100]. The goal of a supervised learning model is to predict the correct label for new input data presented.

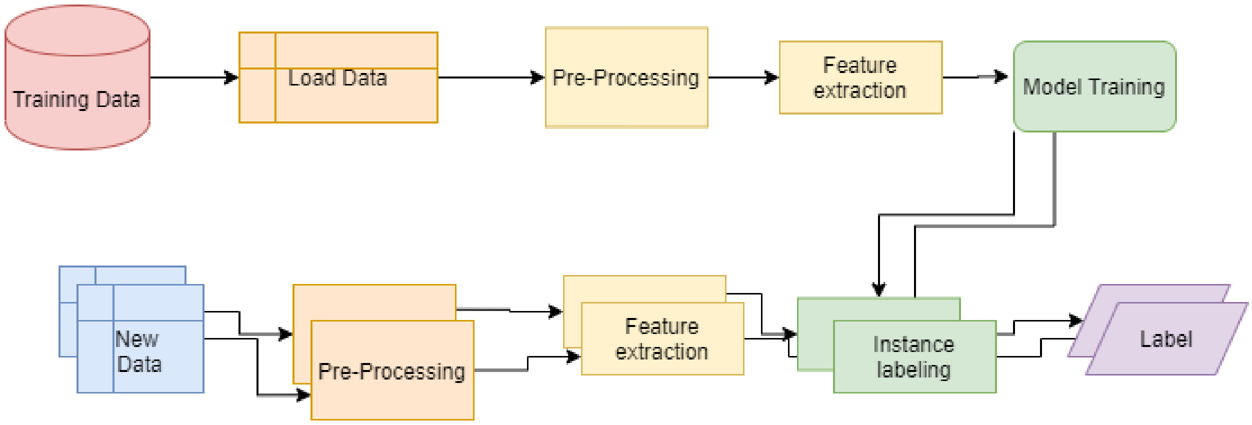

Figure 3.4: Supervised Learning Model

3.3.2 Unsupervised Learning

In the Figure 3.5, through unsupervised learning, a mathematical model is to be built from a data set containing only inputs. Unsupervised learning is used against data that does not contain a historic mark. Association Rules are an example of such algorithms.

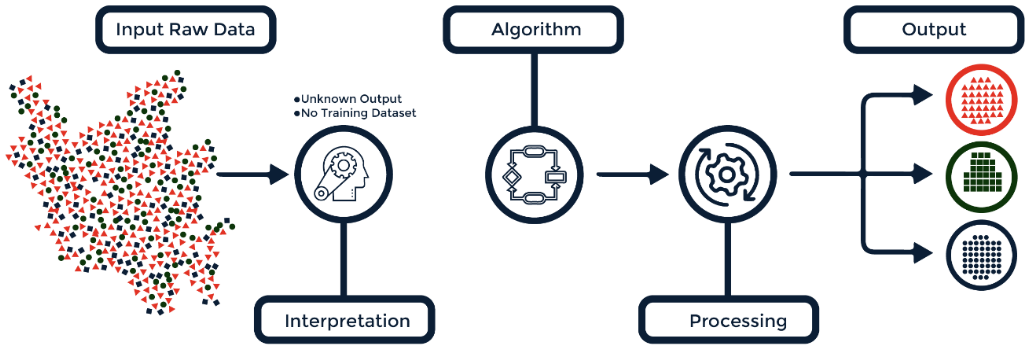

Figure 3.5: Unsupervised Learning Model

3.3.3 Reinforcement Learning

This is the field of learning concerned with how software agents take action in a system to optimize accumulated rewards [100]. Feedback in this type of learning is to be provided in the form of positive or negative feedback in a dynamic environment. They are usually used in an autonomous vehicle or in learning to play a game against a human opponent.

3.4 Deep Learning

Deep Learning was developed from ANN, and now it is an essential area of ML. Deep Learning models use hierarchical structures for connecting their layers. These models use simple linear or non-linear equations to connect the outputs between layers. They make use of low-level features to convert into higher level abstract features. They keep track of the increasingly abstract representations of the input data and have the ability to regularly learn about these factors.

From Figure 3.6, DL works extraordinarily better r than machine learning when it comes to solving complex problems, like speech recognition, image classification, NLP. Deep Learning uses a large number of parameters which makes the training time huge. Classical Deep Learning methods suggest using ANN, CNN, RNN and their altered versions. The softmax classifier is applied upon the deep NN methods to derive the classification output[53].

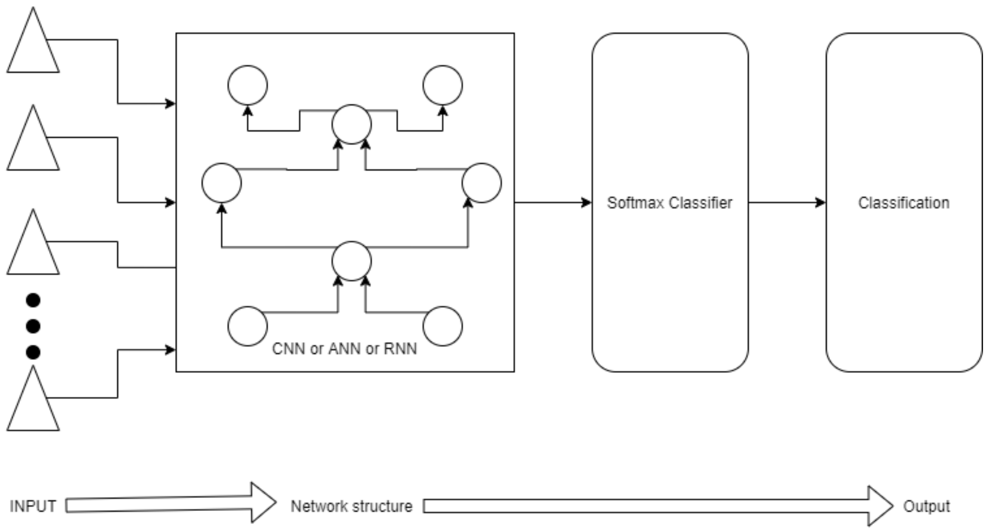

Figure 3.6: Deep Learning Model

3.5 Neural Networks

Neural Networks are multilayer networks which are used for classification, prediction and so on. A NN has an input layer, which provides all the input data and they are passed on to the activation function after assigning individual weights to each of the inputs. The activation function applies the required methods to produce the output that is later passed on to the output layer[61]. There can be multiple hidden layers between the input and the output layer.

Classic NN models suggest feed-forward algorithm which only passes the input data in one direction, towards the output layer . Back-propagation is needed when there is an error signal produced at the output layer. Then the error is returned to previous layers for reduction of error. It is done by the weight update delta rule.

3.6 Convolution Neural Network

A CNN is a particular form of artificial neural network that uses perceptron's, an algorithm for the machine learning unit, to analyze data for supervised learning. Convolutional Neural Network is widely used in the field of Medical science.

Throughout the years plenty of researchers tried to develop a model which can detect the tumor more effectively [87]. A convolution neural network, like other forms of artificial neural networks, has an input layer, an output layer, and multiple hidden layers. Some of these layers are convolution, using a process of mathematics to move findings on to successive layers. It has several layers; including layer of convolution, layer of nonlinearity, layer of pooling and layer of complete relation. The convolutionary and fully-connected layers have parameters, but there are no parameters for pooling and non-linearity layers. The CNN performs outstanding in machine learning problems [51]. Few typical CNN applications, including image classification, object identification, object tracking, pose estimation, text identification and recognition, visual saliency detection, behavior recognition, scene labelling, voice and natural language processing [28]. The CNN architecture that we are using for our classification is VGG16,VGG19 and Inception version 3. Figure 3.7 showed basic CNN architecture.

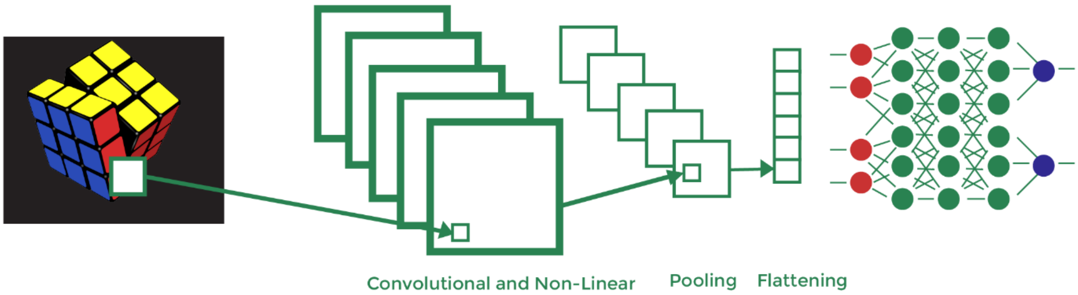

Figure 3.7: Basic CNN architecture

3.6.1 VGG16

VGG is design of a Convolutionary Neural Network (CNN). VGG's key contribution is to indicate that classification / localization accuracy is increased by increasing CNN depth through the employment of little receptive fields in the layers. Neural networks used larger receptive fields before VGG (7 * seven and eleven * 11) compared three—to three * 3 in VGG but they weren't as deep as VGG. There area unit many versions of VGG, the deepest is with nineteen layers of weight. the largest difference among VGG16 and VGG19 is that there area unit sixteen layers in VGG16 and there area unit nineteen layer in VGG19. In VGG19 16 layers area unit convolutional layer and three area unit absolutely connected layer. Figure 3.8 showed VGG16 Architecture.

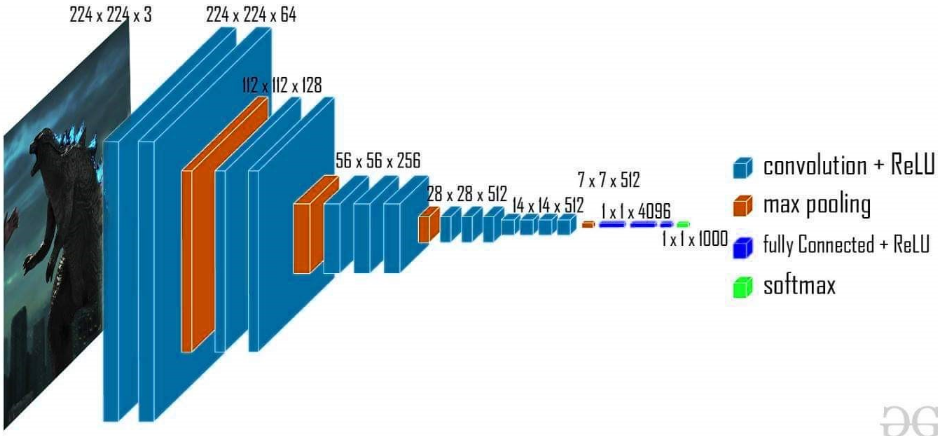

Figure 3.8: VGG16 Architecture

3.6.2 VGG19

There are unit many versions of VGG, the deepest is with nineteen layers of weight. The largest difference among VGG16 and VGG19 is that there are a unit sixteen layers in VGG16 and there are a unit nineteen layer in VGG19. In VGG19 16 layers' area unit convolutional layer and three area unit absolutely connected layer. In VGG19 16 layers area unit convolutional layer and three area unit absolutely connected layer.Figure 3.9 showed VGG19 Architecture.

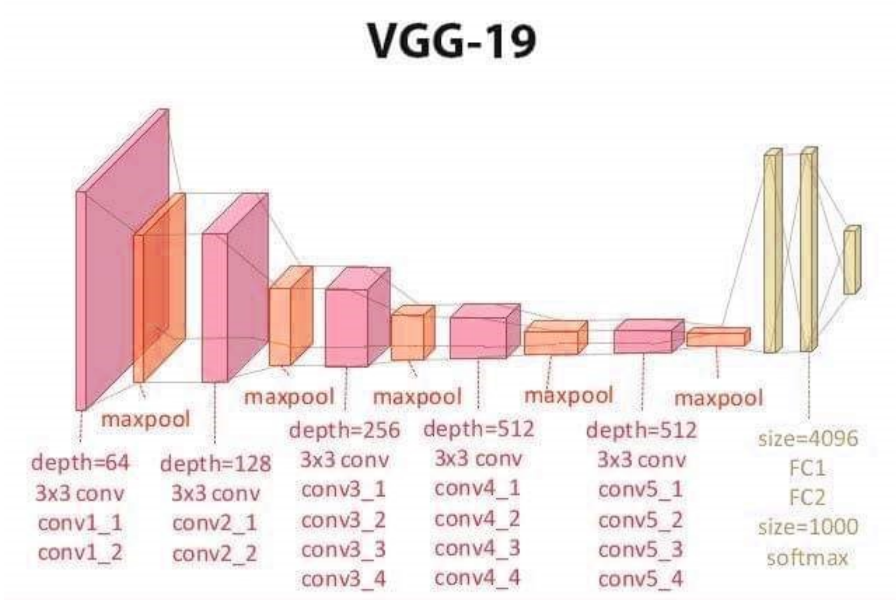

Figure 3.9: VGG19 Architecture

3.6.3 InceptionV3

Inception-v3 may be a convolutionary neural network, trained from the ImageNet information on over 1,000,000 pictures.The network is forty eight layers deep and may categorise pictures into a thousand classes of things, like keys, mouse, pencils and several animals. As a result, the network has learned made representations of options for an oversized type of pictures. . From Figure 3.10, The picture scale of the Network is 299-by-2.

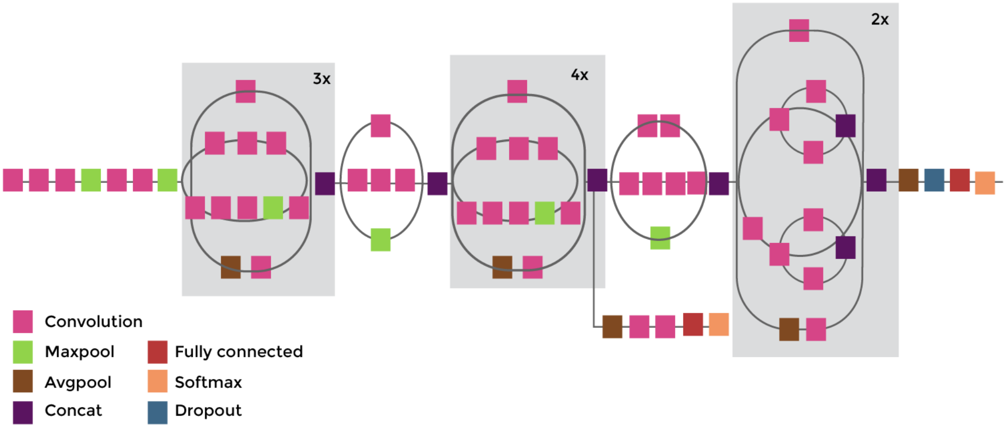

Figure 3.10: InceptionV3 Architecture

3.7 Functional Magnetic Resonance Imaging

Functional MRI is a category of imaging methods designed to illustrate regional and time varying changes in brain metabolism [5]–[7]. fMRI's success stems from its proliferation, non-invasive appearance, reduced cost, and better spatial resolution. Progressively, fMRI is being used as a disease biomarker [16], [23] to monitor therapy [18] or to study pharmacological effectiveness [24]. It is therefore of interest to evaluate the mechanisms of contrast, the strengths and weaknesses and the evolutionary trends of this significant tool. As a brain imaging technique, fMRI has many major advantages: it is non-invasive and does not require radiation, making it safe for the patient, has excellent spatial and decent temporal resolution, as well as being easy to use for the experimenter.

fMRI works by identifying changes in blood oxygenation and flow that results in response to neuronal activity – when a brain region becomes more active, it absorbs more oxygen and the blood flow increases to the active area to satisfy this increased demand. FMRI can be used to provide activation maps showing which brain parts are involved in a particular mental phase. Oxygen in capillary red blood cells is supplied to the neurons by hemoglobin. There is an increased demand for oxygen if neuronal activity of the brain increases. And the local response is increase in blood circulation regions with accelerated brain function.When oxygenated, hemoglobin becomes diamagnetic, but when de-oxygenated it becomes paramagnetic. Such variation in magnetic properties results in slight changes in blood's MR signal depending on the degree of oxygenation. Since blood oxygenation differs based on the neuronal activity levels, these variations can be used to detect brain activity.

CNN has attracted much attention in recent years and has been commonly used in fMRI data processing, as relevant features can be extracted automatically [40], [48].

For example, CNN has been used to classify fMRI data effectively [40], and to identify and diagnose Alzheimer's disease (AD) and aMCI. The CNN method consists of the following three applications: feature extraction, auto-encoder construction, and 3D CNN construction. Restricted Boltzmann Machine (RBM) and Deep Boltzmann Machine (DBM) are also used to evaluate fMRI data, in addition to the commonly used methods mentioned above.

3.8 Lobe

As we know, detecting tumor as its early stages increases the chance for a better treatment and cure. There are so many unpleasant symptoms that we are experiencing in our day to life. Those annoying syndromes grows along with tumor's size and started to affect the function of the brain part. Additionally, these breakdowns give the evidence of having brain tumor and helps the doctor to understand where the tumor might be located. Those annoying symptoms indicated the location of the tumor in our brain. There are four main Lobes in our brain namely frontal, parietal, temporal, and occipital lobes.A picture of Frontal Lobe is showed in 3.11 , Parietal Lobe picture is showed in 3.12 and Temporar Lobe image is showed in Figure 3.12.

3.8.1 Frontal Lobe

Frontal Lobe is located behind the forehead area of the brain's cerebral cortex. In the paper [12], there have been studies on frontal Lobe syndromes and have found some maladies, are mentioned below:

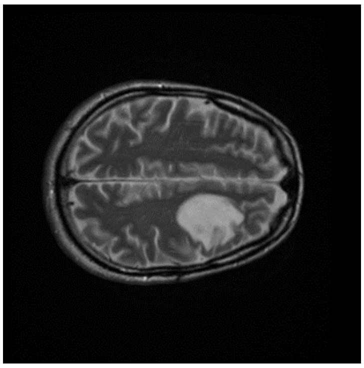

Figure 3.11: Frontal Lobe

1. Aphasia and Agraphia: Aphasia is a speech disorders that snatch the ability to communicate and Agraphia writing disorders that affect the writing ability.
2. Apraxia: Apraxia is a disorder that hamper the ability of movements. For example: walking difficulty.
3. Dyslexia: Slow down the function of brain. For example: Reducing the ability of sight-reading.
4. Oculomotor apraxia: Oculomotor apraxia is a vison disorder that seize the ability of eye movement and control.

5. Interoreflex and neurosecretory: These disorders affect emotions, reactions, and Moods.

3.8.2 Parietal Lobe

The parietal lobe is one located between the central furrow and the occipital ridge and helps process the sense of touch and pain [52]. In the paper [63], the authors have focused on parietal Lobe syndromes and have justified some indicators that help the people to aware of parietal located brain tumor, indicators are given below:

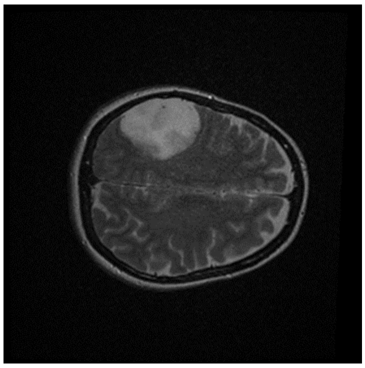

Figure 3.12: Parietal Lobe

1. Impaired consciousness and thinking way: Such a condition where peoples have no signs of being awake and no signs of being aware; and lose thinking ability.

2. Perception and sensation disorders: Sensory disorder is an illness that affect sensory cognitive processes. Perception disorder kill the ability of percept information and recognize the stimuli acting on the sense. For example: unable to detect touch (warmth, cold and pain); the sense of sight, hearing, smell, taste, sense of time, direction, etc.

3. Motor disorders: Discontinuity in nervous system. For example: gross motor skill difficulties (i.e. jumping); nail-biting, hitting own self.

4. Disorders of spoken speech: Having difficulty in speaking and understanding.

3.8.3 Temporal Lobe

Temporal Lobe is located in each brain hemisphere involved with memory and hearing [27]. In the paper [65], the researchers have conducted an experiment on Temporal Lobe syndromes and have explored remarkable testimony, are inclined below:

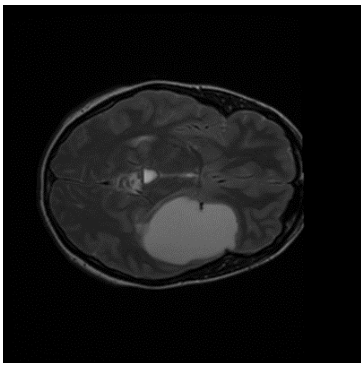

Figure 3.13: Temporal Lobe

1. Feeling of disturbed in mood and emotions.
2. Hearing problem.
3. Visual impairment.
4. Behavioral changes.
5. Forgetting habit; short-term and long-term memory loss problems.

3.8.4 Occipital Lobe

The occipital lobe is located in the posterior area, part of the cerebral cortex. Wang, An-Guor at el [78] conducted an experiment on a 72 years old female who had left occipital meningioma Tumor. The female had experienced unpleasant activity, are represented below:

1. Apprehended intolerable headaches and dizziness.
2. Vison problem in one or both eyes.
3. Failed to recognition color.
4. Unable to object movement.

3.9 Brain Tumor Detection by CNN

Detection of brain tumors could be a great support for doctors and a blessing for medical imaging by CNN.CNN technology demonstrates superior potency in classification sectors. The level of classification of CNN tumor pictures was more than that of ancient classification method [98].

Like neural networks, CNNs are composed of neurons with learnable weights and biases. Every nerve cell receives multiple inputs, takes over them a weighted total, passes it through associate activation operate associated responds with an output [96]. The sole purpose of selecting CNN rule for sleuthing higher tumor is that it generates a better accuracy level.

The tumor is understood joined of the harmful diseases which will occur on any a part of the body which suggests the body's abnormal form or lump on the part. Brain tumor is that the most dangerous wherever the tumor is within the brain and is incredibly exhausting to cure. The tumor is known as one of the dangerous diseases that can occur on any part of the body which means the body's abnormal shape or lump on the part of the body. Brain tumor is the most dangerous where the tumor is inside the brain and is very hard to cure. These unhealthy cells will affect healthy cells in the brain which make those more dangerous [89].

One of the main difficulties for identifying and segmenting brain tumors is the collection of features. There are several revolutionary methods in processing features that, at the same time, are proven to improve the precision for identification and segmentation of brain tumors. Multiple models are commonly used in previous studies, such as SVM and NN [44]. The human brain is built on using neural network's design and implementation. The neural network is used especially for approximation, vector quantization, data clustering, functions for optimization, pattern matching and techniques for classification [83]. Image cannot be scalable within the normal neural network. But image can be scalable in CNN, i.e. it will take 3D input volume to the 3D output volume (length, width, height). CNN can be used to achieve good image processing accuracy by avoiding pre-processing and can automatically learn complex features from images [55].

CNN methods have become popular in image processing and greater concern has been paid in the gray scale images. As CNN is an array of processors with analog dynamics, the gray scale image therefore includes analog pixel values, which can be processed directly using CNN. In addition, CNN can be used in applications such as high speed target recognition, motion detection, and visual inspection in real time, image segmentation, pattern recognition, and also information processing tasks [21]. Deep CNN has a powerful learning capability as it uses multiple extraction stages of features. These features can automatically run about the representations of data. Development of CNN has been boosted by the availability of a large amount of data and hardware technology development, and deep CNN architectures have been documented recently. Numerous groundbreaking ideas have been studied to introduce advancements in CNN, such as using different activation and loss functions, optimization of parameters, regularization and architectural innovation etc. CNN has made some glorifying progress in image processing and vision related tasks. Therefore, CNN has restored researchers' interest in ANNs. Activation, loss function, optimization, regularization, learning algorithms and architectural innovations are some of the major improvements of CNN [90].

Chapter 4

Proposed Model

In this paper we are working accordingly to the workflow diagram Figure (4.1). In the process of identifying brain tumor, at first we have collected our data from UK Data Service Reshare (http://reshare.ukdataservice.ac.uk/851861/) that contains 22 patients brain tumor history such as
Id, Sub-D, pathology, tumor location, Volumes, DES result, axial image, resting state and tissue
classes etc. Our proposed system's main goal is to detect tumor tissue at an early stage so that tumors treatment can be provided as soon as possible to the patients for flourishing the chances of being cured. In this section, we are tried to explain our full work procedure of proposed brain tumor classification scheme based on the basic architecture namely VGG16, VGG19 and Inception V3 of CNN. Firstly, we divided our data into two class namely "yes" class and" no" class for performing binary class classification, later on divided on 5 class namely "Frontal Lobe" region," Parietal Lobe" region," Temporal Lobe" region," Occipital Lobe" region, and" No Tumor "class for doing region based classification. Finally, we end up our classification by implementing four position based classification consists of four class namely "Front Right" position, "Front Left" position, "Bottom Right" position, "Bottom Left" position for constructing brain position based classification. Our proposed model runs by six steps for ensuring better testing accuracy and performance of the classifiers by comparing three types classification using three types of architecture of CNN.

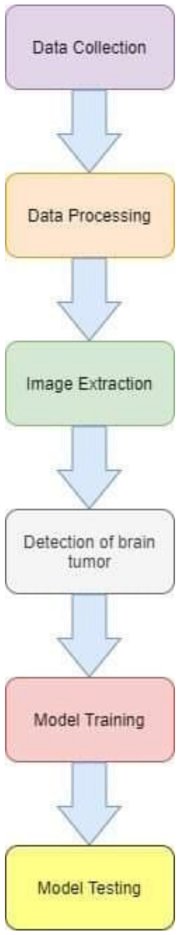

Figure 4.1: Work Flow for Detection of Brain Tumor

4.1 Data Collection

We have collected data from our data set. From the information set we came up with some info that square measure given below. The data presented here were acquired as part of a pilot study investigating the feasibility and usefulness of functional magnetic resonance imaging (fMRI) for surgical brain tumor planning. Brain imaging results are available from 22 patients with brain tumors. Alongside clinical details, these include T1, T2, DTI, and functional MRI data. The data were acquired as part of a pilot study investigating the effectiveness and usefulness of functional magnetic resonance imaging (fMRI) for surgical brain tumor planning.

The Repository collects information from twenty-two patients. Each patient is marked with a singular assortment of random strings (ID and sub-ID) that's easier for USA to find them on an individual basis. Data of patients with the topic ID square measure organized in tar files. Each tar file contains a sub-ID folder about the examination data that refers to the date of the analysis and includes image data, contained in separate nada files. the information therein nada file is in normal Nifti (.nii) format. The scanner's original DICOM files were separated from personal information, so changed using dcm2nii. The structural photos (T1 and T2) have used SPM12 as traditional. Useful MRI (single-shot gradient-echo echo-planar) image sequence with field-of-view 256 x 256 millimeter ,slice thickness four millimeter, thirty slices per length, interleaved slice order, acquisition matrix sixty four x sixty four, and TR = 2.5 s, flip angle= ninety degrees and echo time fifty MS) useful image information consisted (depending on patients) of 1 motor run, on one word repetition run (mapping of brain doctor area), One verb generation run (mapping space of Broca and Supplementary Engine Area) and one rest state run. The sequence descriptions are kind of like the information collected within the management subjects used for protocol testing and might be found in' A test-retest functional magnetic resonance imaging dataset for motor, language and spatial attention functions.

From the data sets we have required some information about the male female ratio. There were altogether 22 number of people in the data set (see Table 4.1). Where the male candidates are high in number. There were people from different age group in the data set which is shown in the scatter diagram.

Table 4.1: Patient Information

Subject ID	Age	Gender
17904	43	Male
18428	26	Female
18638	35	Female
18675	68	Male
18863	75	Male
18886	41	Male
19085	28	Female
19277	31	Male
19398	65	Female
19423	40	Female
19567	42	Male
19723	27	Female

This is a raw image showed in Figure 4.2 from the data set that is in 3D.

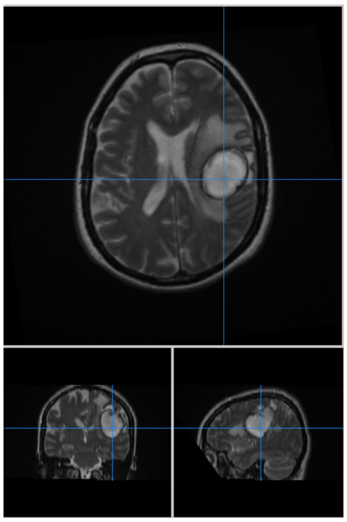

Figure 4.2: fMRI Image of a patient(3D)

4.2 Data Processing

After collecting our data we have processed it by applying some factors. One of those are image conversion. We have converted the 3D images to the 2D images as we are applying neural networking here and neural network works in 2D. The factors that we have used is data augmentation and data normalization for image conversion from 3D to 2D. We have done data processing for all our classifications that includes binary classification, five Class Brain Lobe Classification,4 position classification. The factors are given below-

4.2.1 Data Augmentation

Modern neural network training relies heavily on data augmentation for greater generalization [101]. In deep learning models, the quantity and complexity of data obtained to recent years have been largely related. Data augmentation is a technique that enables practitioners to increase the variety of data available for training models substantially, without actively collecting new data. Techniques for rising data such as cropping, folding, and horizontal flipping are widely used to train extensive neural networks. Most methods used in training neural networks, however, use only specific forms of augmentation. Although the neural network architectures were studied in detail, less emphasis was focused on discovering strong types of data increase and data increase policies that catch data invariances [86].

We have used augmentation in all our classifications- binary classification, five class brain lobe classification,4 position classification. Each of the axial images were prepared for data augmentation. We are applying data augmentation so that it can identify any image vertically, horizontally or a version of a stretched image. While doing binary classification we tried to bring variety in the images through augmentation process. After doing augmentation on the axial images we tried to classify each of the angle. In the five class with brain lobe classification, after generating augmentation we got are Frontal Lobe, Parietal Lobe, Occipital Lobe, Temporal Lobe and No tumor. We have found that frontal lobe class consists of 8 patients' data, parietal lobe, occipital lobe, temporal lobe and no tumor class contains 9 patients' data, 0 patients' data, 2 patients' data and 3 patients' data respectively. We differentiated classes according to the tumors position in the brain. The front-right, bottom-right, front-left and bottom-left. After that, data augmentation is simulated through the images. While we perform a data augmentation for learning deep neural networks, it is important for training visual recognition systems. It artificially increases the number of training examples. Therefore, it helps reducing overfitting or improves generalization. Data augmentation makes the images ready for applying algorithms. This is how we used augmentation in all the three classifications.

4.2.2 Data Normalization

Normalization is the method most used for analyzing data. It aims to build a collection of images with minimal data redundancy. Moreover, it will maintain consistency and encourage accurate insertion, deletion and alteration. Owing to future upgrades, a simplified data does not display any anomalies. Using an automated technique to do this data is very time consuming [17]. It is a very important technique of preprocessing data without which analytics are poured into solutions that hit inconsistencies [75].

The 3D images that we went through the normalization process that breaks each of the images into many different slices. Each of the slices were the images of axial state of brain. It helps us for further classification. It provides a structural form of data by organizing it. By breaking the image into slices we have used normalization for binary classification, five Class Brain Lobe Classification,4 position classification.

4.3 Image Extraction

We have transformed the 3D images to the 2D images using the Nibabel library. The 2D image (Figure 4.3) shows the image that we got after applying data augmentation and normalization process. By applying data normalization and augmentation we have got the 2D images for classification purpose.

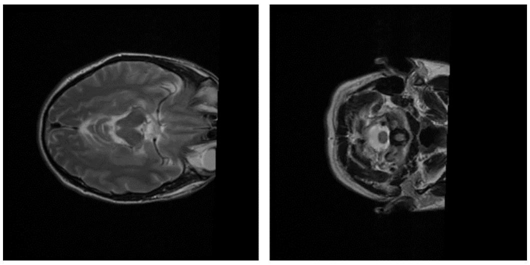

Figure 4.3: fMRI Image of a patient(2D)

4.4 Detection of Brain tumor

After applying all the above factor we finally get the 2D image. Then from the image we can finally detect the brain tumor. The acquired image from (Figure 4.4) shows us that there is tumor in the brain. On the other hand, the image (Figure 4.4) shows that there is no brain tumor of the image. By monitoring the images, we can clearly say that which patient have brain tumor and which has not brain tumor.

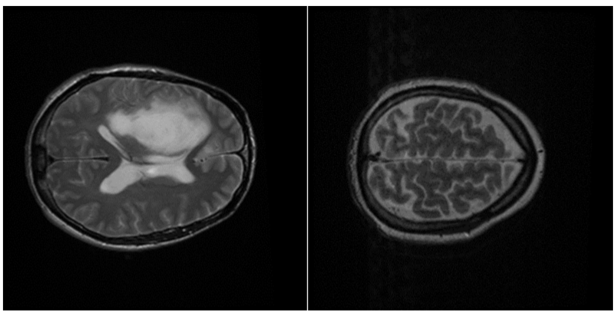

Figure 4.4: Detection of brain tumor of a patient in 2D image

4.5 Model Training

After applying all the above factors, the images will be divided into two directory one of these are model training. There are three classifications that we have used in the model training. For binary classification there are two sub folders named "yes" "no" that contains the information if a patient has brain tumor or not (Figure 4.6). Five Class Brain Lobe Classification contains five groups which are Frontal Lobe, Parietal Lobe, Occipital Lobe, Temporal Lobe and No tumor. Apart from the no tumor class there are four other classes what have been created while performing five class classification. Taking images from the four lobes we have done four position classification that is front-right, bottom-right, front-left and bottom-left. The four position classification helps us to location the position the exact location of brain tumor.

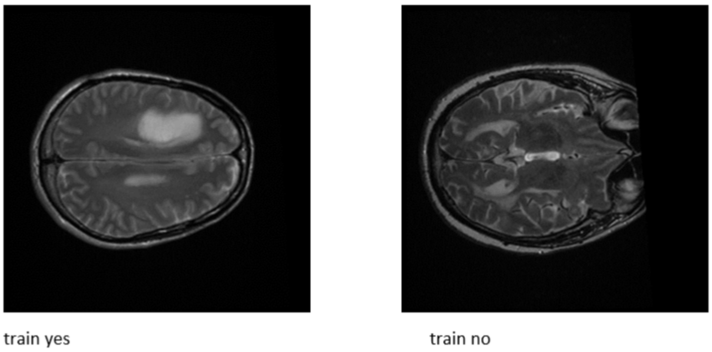

Figure 4.5: Training model for binary classification.

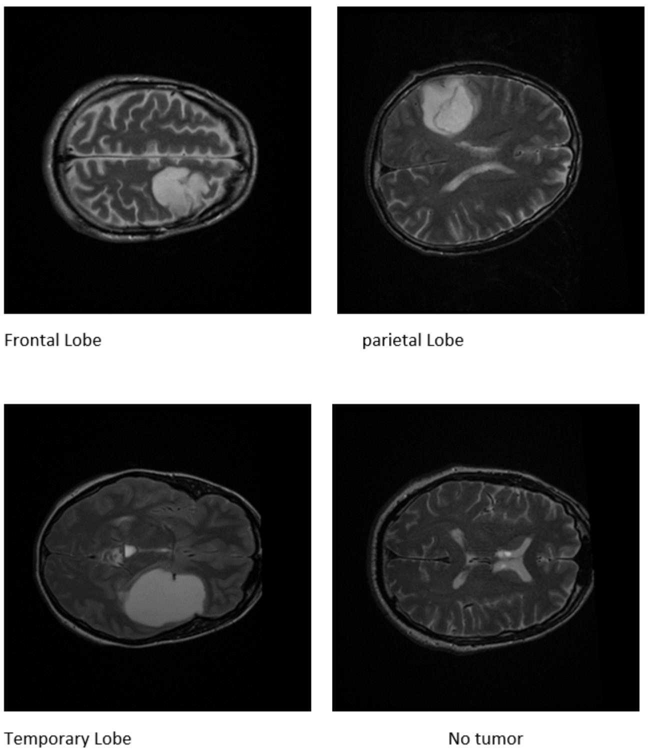

Figure 4.6: Training model for Five Class Brain Lobe Classification

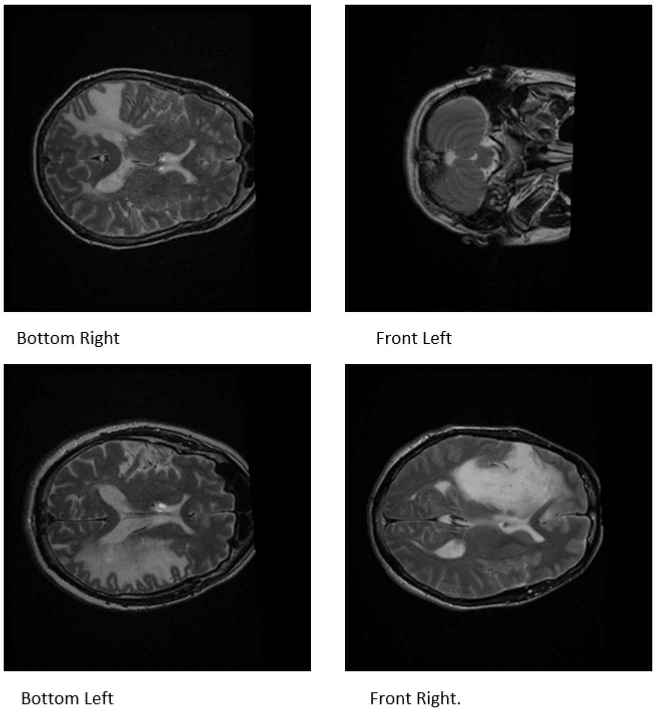

Figure 4.7: Training model for 4 position Classification

4.6 Model Testing

The model testing phase is used for accuracy detection. The higher the accuracy the better it is. After sorting entire data, we apply various CNN architecture in the testing phase. We have applied all the three classification for the testing phase. Testing model for binary classification images are showed in Figure 4.8, Testing model for Five Class Brain Lobe Classification images are showed in Figure 4.9, and Testing model for 4 position Classification images are showed in Figure 4.10.

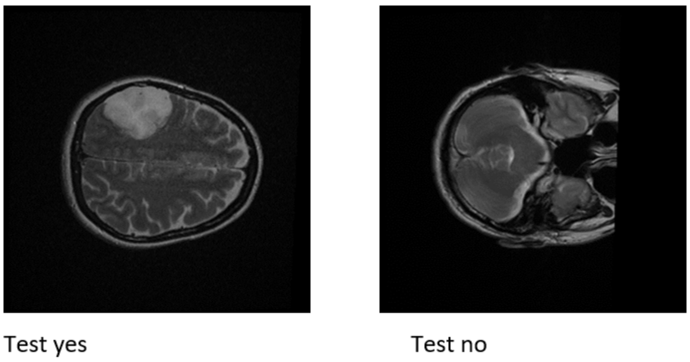

Figure 4.8: Testing model for binary classification

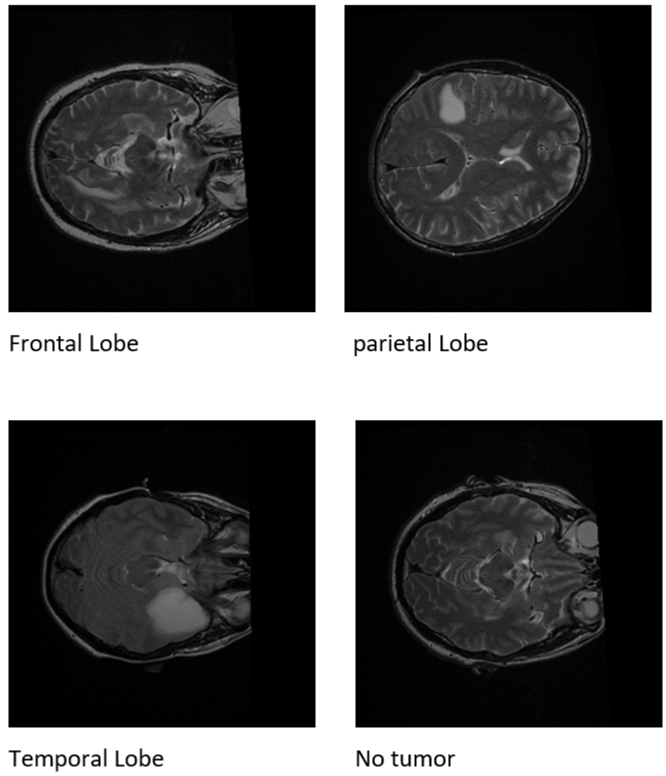

Figure 4.9: Testing model for Five Class Brain Lobe Classification

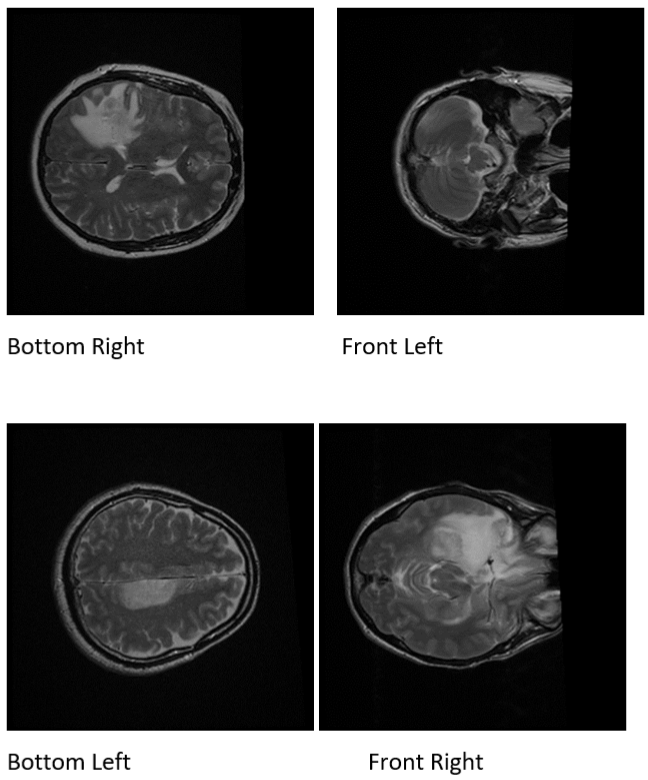

Figure 4.10: Testing model for 4 position Classification

4.7 CNN Architecture

Once all the data are sorted by the model training and model testing will be trained. In the model training, we have used CNN algorithm. In the binary classification the number of epochs is 10. There were 20 images in each batch. Basically, the batch size is 20. For five class brain lobe classification and four position classification number of epochs are 7. There are 10 iterations in per epochs. The architectures we are using are VGG16, VGG19 and InceptionV3 of CNN. We have used softmax and ReLu as activation layer function.

`categorical_Crossentropy` is used as the loss function. The activation layer that is used in our CNN algorithm is the soft max and Rectified Linear Unit (ReLU). Softmax is an application algorithm-that normalizes a complex distribution-from K number of functional concatenations of composites. Instead of having a set where the values can be anything—0, -1, 1, 2, etc. A unit-which is designed to correct and compensate for errors in signal parsing-like when we need to encapsulate epsilon (infinitely small)-and we need to work around that. But ReLU "Steers the signal back" to where it will go — so that the signal doesn't burst or disappear.

Categorical Crossentropy

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

$$CCE = -\frac{1}{N}\sum_{t=0}^{N}\sum_{j=0}^{j} y_j.\log(\underset{Y_j}{\rightarrow}) + (1 - Y_j).\log(1 - \underset{Y_j}{\rightarrow})$$

Categorical Cross entropy's code image are showed in Figure 4.11.

```
optimizer =tf.keras.optimizers.Adam(lr=1e-5)
loss = 'categorical_crossentropy'
metrics = ['accuracy']


def print_layer_trainable():
    for layer in conv_model.layers:
        print("{0}:\t{1}".format(layer.trainable, layer.name))


print_layer_trainable()


new_model.compile(optimizer=optimizer, loss=loss, metrics=metrics)
```

Figure 4.11: categorical Crossentropy

Softmax

- It is used in output layer
- Softmax is an activation function that is used for testing accuracy purpose.
- The softmax classifier is applied upon the deep NN methods to derive the classification output.

$$f_i(\vec{a}) = \frac{\epsilon^{a_i}}{\sum_k e^{a_k}}$$

Softmax's code image are showed in Figure 4.12.

```
# Add a dropout-layer which may prevent overfitting and
# improve generalization ability to unseen data e.g. the test-set.
#new_model.add(Dense(512, activation='relu'))


# Add the final layer for the actual classification.
new_model.add(Dense(num_classes, activation='softmax'))
```

Figure 4.12: Activation Layer of "Softmax"

ReLU

- It transforms the linear form into a non-linear form.
- It also works to generate testing accuracy.
- It generates the value between 0-1.
- It is used in hidden layer.
- The equation for this layer is,

$$RELU(x) = \begin{cases} 0 & if \quad x < 0 \\ x & if \quad x \geq 0 \end{cases}$$

ReLU's code image are showed in Figure 4.12.

```
new_model.add(Flatten())

# Add a dense (aka. fully-connected) layer.
# This is for combining features that the VGG16 model has
# recognized in the image.
new_model.add(Dropout(0.5))

new_model.add(Dense(1024, activation='relu'))
```

Figure 4.13: Activation Layer of "ReLU"

Chapter 5

Results and Analysis

Evaluation of performance of a model merely depends on some attribute namely Epoch accuracy, Testing Accuracy and Loss Function. In illustrate, Selecting the highest value from per epochs considered as an Epoch accuracy, testing accuracy gives an overview of correctness rate of a system and loss function explains that how far we are from our expected model performance and it used for determining the systems error. In our experiment, we expected least loss function and higher epoch and testing accuracy to validate and improve the performance of our preferred model. At the end of the experiment, we come up with three classification named binary, five class classification based on region and four position classification by using 3 different architecture of CNN and those are VGG16, VGG19, Inception V3 for setting up a comparison among them that will help use to understand which classification and which architecture can obtain highest accuracy and better performance. Here, we tried to give some evidence such as table and graph for comparing each classification and architecture to another.

5.1 Binary Classification Epoch Accuracy

Table 5.1: Accuracy of detecting brain tumor using VGG19

epochs	Accuracy									
1	79.32									
2	78.11	82.55								
3	82.67	83.32	82.57							
5	83.60	84.21	84.56	84.88	85.32					
7	85.38	86.69	86.03	90.15	86.83	86.83	89.50			
9	89.34	90.63	92.97	93.70	93.70	93.30	93.62	81.66	89.75	
10	93.30	95.40	95.15	93.62	94.75	94.91	94.35	94.51	92.49	95.07

In the Table 5.1, we found the accuracy of detecting a brain tumor when using a CNN's architecture VGG19. We run 10 epochs in VGG19. And for each epoch we got an accuracy. While running the 1st epoch the accuracy we got was only 79.32%. But in the 2nd epoch it increased to 82.55%. Similarly, on the further epochs the accuracy increased. The highest accuracy we were able to obtain was 95.40% while using VGG19.

Table 5.2: Accuracy of detecting brain tumor using VGG16

epochs	Accuracy									
1	81.91									
2	82.31	79.89								
3	77.79	78.92	82.55							
5	83.52	83.20	86.51	88.13	86.11					
7	85.54	92.16	88.53	91.44	91.76	93.13	93.62			
9	92.41	94.10	92.65	92.81	93.56	95.07	93.34	94.18	94.18	
10	94.99	95.72	95.23	94.75	92.89	95.64	94.59	94.02	95.23	96.04

In the Table 5.2, we found the accuracy of detecting a brain tumor when using a CNN's architecture VGG16. Similarly, we run 10 epochs in VGG16 as well. While running the 1st epoch the accuracy for detecting the brain tumor was 81.91%. While running the 5th epoch we were able to get the accuracy up to 88.13%. And the highest accuracy we could obtain while using VGG16 was 96.04% which was in the 10th epoch.

Table 5.3: Accuracy of detecting brain tumor using InceptionV3

epochs	Accuracy									
1	71.57									
2	80.78	76.74								
3	78.43	72.29	83.52							
5	85.70	92.97	92.97	91.76	94.51					
7	83.60	84.09	88.45	87.40	87.72	91.11	91.52			
9	92.16	92.49	92.57	92.25	94.10	91.20	91.84	92.16	93.62	
10	92.49	94.83	95.40	95.23	92.41	94.83	92.25	93.46	93.73	94.75

Running the 1st epoch we got the accuracy 71.57% for detection of tumor in a brain. The accuracy drastically increased in the 2nd epoch to 80.78%. And after further running the epochs at the 10th epoch we were able to obtain the highest accuracy of 95.40%.

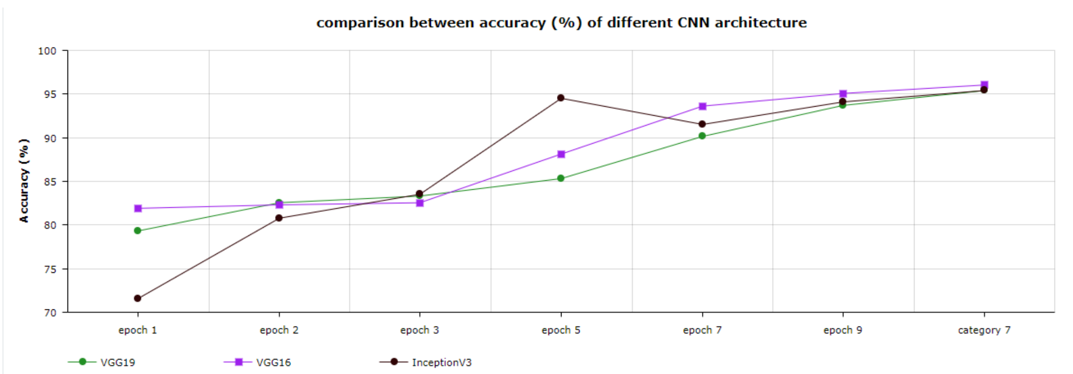

Figure 5.1: Comparison between accuracy of different CNN architecture

In the Figure 5.1, we can see the comparison between the VGG19, VGG16 and InceptionV3. We took the highest accuracy of an epoch and plot it. Accuracy varies from each architecture. As we can see from the graph, in the 1st epoch VGG19 give an epoch accuracy of 79.32%, the VGG16 give an epoch accuracy of 81.91% lastly InceptionV3 gives an epoch accuracy of 71.57%. So we can say InceptionV3 is the worst in case of 1st epoch. in the 2nd epoch the highest accuracy from running the epoch 2 time we get for VGG19 in 82.55%, for VGG16 is 82.31% and for InceptionV3 we get 80.7%. In the 2nd epoch VGG19 has the highest epoch accuracy of 82.55%. Furthermore, in the 3rd epoch the highest epoch accuracy for running the epoch 3 time we get the highest epoch accuracy for VGG19 is 83.32%, for VGG16 in 82.55% and for InceptionV3 83.52%. Here InceptionV3 has the highest accuracy. In the 5th epoch we can see that the accuracy increased a lot. Like for VGG19 architecture the highest epoch accuracy is 85.32%, for VGG16 the highest epoch accuracy is 88.13% and for InceptionV3 the highest epoch accuracy is an outstanding 94.51%. In the 5th epoch InceptionV3 accuracy is much higher than any other architectures. For the 9th epoch we can see that the highest accuracy for the VGG19 architecture 93.70%, for VGG16 is 95.07% and lastly for InceptionV3 the highest epoch accuracy is 94.10%. So in the 9th epoch the VGG16 has the highest accuracy. Lastly for the 10th epoch we can see the highest epoch accuracy for VGG19 is 95.15%, for VGG16 is 96.04% and for InceptionV3 the highest epoch accuracy is 95.40%. So, in the 10th epoch the highest epoch accuracy between the three architecture VGG16 has the highest epoch accuracy. The highest epoch accuracy we have acquired from all the three architecture is 96.04% which is obtained from VGG16.

Table 5.4: Testing Accuracy and Loss Function

epoch	Test Accuracy (%)			Loss Function (%)		
	VGG16	VGG19	inceptionV3	VGG16	VGG19	InceptionV3
1st	76.32	80.85	78.39	39.57	41.88	64.32
2nd	86.65	93.78	80.62	14.93	15.23	56.28
3rd	89.86	95.71	81.79	11.20	12.08	34.08
4th	90.79	95.07	83.48	10.78	11.02	26.33
5th	91.55	97.09	86.34	9.65	8.51	20.89
6th	92.42	96.76	89.07	9.13	8.26	17.82
7th	94.86	98.68	91.26	8.84	5.28	14.26

The Table 5.4 represent the testing accuracy and loss function of three architecture. Using VGG16, first epoch able to scored lowest test accuracy is 76.32% and highest loss function is 39.57%. If we noticed 4th epoch, this epoch obtained 90.79% test accuracy and 10.78% loss accuracy that means epoch accuracy is increasing step by step as well as loss function decreasing as the testing accuracy rate is in increasing way. In the last epoch, it gains 94.86% epoch accuracy and 8.84% error in our model. Initially, 80.85% testing accuracy and 39.57% loss function recorded while VGG19 is applied to the model. Moreover, in 2nd, 3rd, 4th, 5th,6th and 7th epoch VGG19 achieved 93.78%, 95.71%, 95.07%, 97.09%, 96.76% and 98.68% testing accuracy respectively and 41.88%, 15.23%, 12.08%, 11.02%, 8.51%, 8.26%, 5.28% loss function respectively. For inception V3, lowest accuracy recorded 78.39% and loss function is 64.32%. Considering 4th epoch of inception V3 architecture, we can see that 83.48% testing accuracy and 26.33% loss function obtained. For epoch 5th, 6th and

7th, testing accuracy obtained 86.34%, 89.07%, 91.26% and loss function 20.89%, 17.82%, 14.26% respectively. The highest testing accuracy obtain from VGG19 and lowest testing accuracy obtained from inception V3 whereas VGG19 accords lowest lost function and inception V3 obtained highest loss function. The highest Test accuracy rate is 98.68% and error is 5.28%. Thus, we can claim that VGG19 is the most preferable architecture in Binary classification.

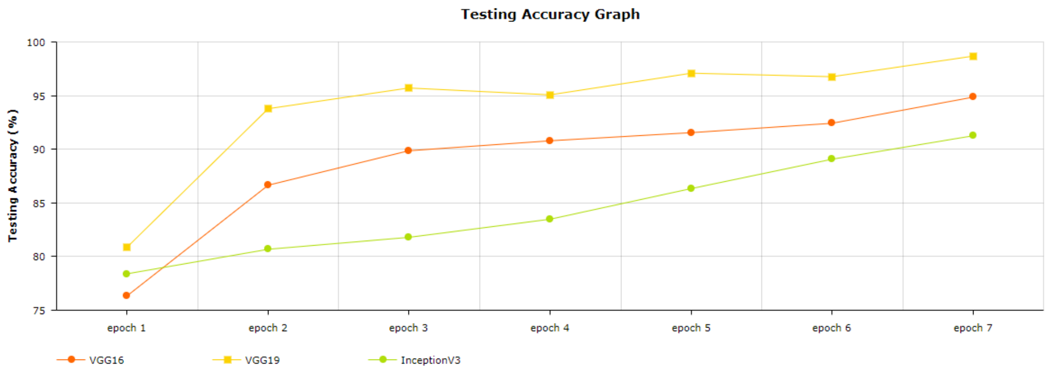

Figure 5.2: Testing Accuracy

Figure 5.2, delineating testing accuracy comparison between basic CNN architecture of VGG16, VGG19 and Inception V3. We found that VGG19 provides the highest accuracy which is 98.68% and inception V3 provides the lowest accuracy rate which is 91.26%.

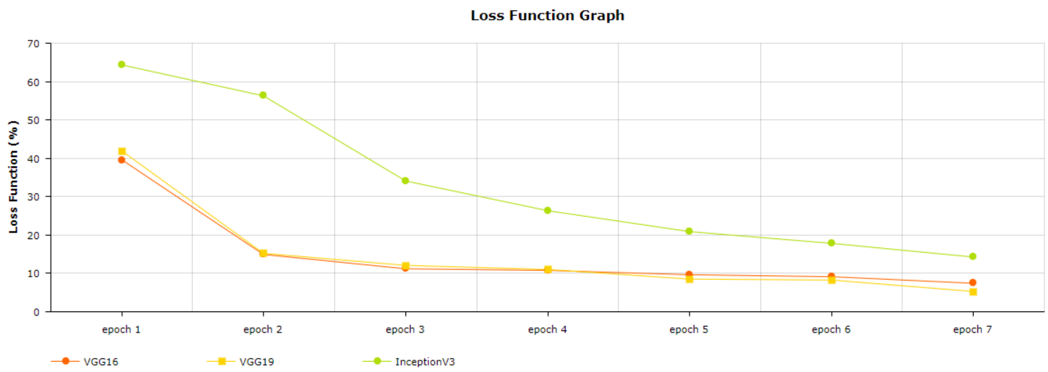

Figure 5.3: Loss Function

The graph showing in Figure 5.3, representing percentage of error comparison between different architecture of CNN. We noticed that VGG19 produced least amount of error that is 5.28% and inception V3 produced maximum number of Loss Function is 14.26%.

5.2 Five Class Classification Epoch Accuracy

Table 5.5: VGG16 Epoch Accuracy Table

Epoch	Accuracy in Percentage									
1st 10	39.29	45.92	50.69	48.69	47.7	41.91	46.38	42.53	42.06	47.46
2nd 10	49.61	49.77	51.62	47.46	52.23	58.24	53.31	56.09	58.09	59.94
3rd 10	61.17	58.55	59.94	58.55	61.17	56.09	63.02	67.33	67.80	66.41
4th 10	67.95	67.18	67.49	65.49	58.86	72.42	68.88	72.42	69.34	73.19
5th 10	66.72	67.80	71.19	75.04	72.42	73.65	73.04	73.96	73.50	72.57
6th 10	64.56	74.11	73.04	74.27	75.04	76.43	73.65	67.95	76.43	72.57
7th 10	73.96	75.50	74.58	78.89	71.03	78.58	75.04	73.34	76.89	78.12

In Table 5.5, representing the epoch accuracy rate using VGG16 architecture. From the first 10 epochs, we got the accuracy is 50.69%. After initiating seventh 10 epochs, we got the highest accuracy rate is 78.8%. The accuracy rate increased in every step, from 1st to 7th 10 number epochs.

Table 5.6: VGG19 Epoch Accuracy Table

Epoch	Accuracy in Percentage									
1st 10	38.52	38.37	47.00	38.98	48.07	40.52	45.61	30.82	41.76	38.98
2nd 10	50.23	41.60	43.45	54.55	52.08	53.93	55.47	40.99	56.09	44.38
3rd 10	47.30	60.09	58.55	58.40	60.09	49.00	51.62	63.79	63.17	54.24
4th 10	64.57	60.55	64.71	63.79	61.63	65.33	58.86	65.18	58.86	61.94
5th 10	67.33	60.25	70.26	65.33	68.72	64.10	63.94	67.49	63.48	70.72
6th 10	74.27	62.40	72.73	64.10	65.79	70.88	54.24	70.57	73.34	71.49
7th 10	76.43	74.11	65.79	70.26	73.34	68.10	72.88	79.82	78.58	77.81

The preceding Table 5.6, representing the epoch accuracy rate using VGG19 architecture. From the first 10 epochs, we got the accuracy is 48.07%. After initiating seventh 10 epochs, we got the highest accuracy rate is 79.82%. The accuracy label increased step by step.

Table 5.7: Inception V3 Epoch Accuracy Table

Epoch	Accuracy in Percentage									
1st 10	43.30	40.83	44.38	39.75	47.92	43.91	45.30	50.85	44.99	48.84
2nd 10	41.91	50.23	50.08	46.84	49.31	49.77	48.54	49.46	50.23	47.15
3rd 10	45.61	49.61	50.08	50.23	47.46	44.53	51.46	49.15	53.31	47.15
4th 10	47.00	45.45	46.69	51.46	49.31	48.07	50.69	46.53	53.47	45.15
5th 10	55.01	49.00	53.47	55.78	54.55	54.08	57.78	53.47	54.85	57.16
6th 10	56.70	61.33	59.48	59.48	60.40	61.33	62.10	60.09	63.64	62.56
7th 10	62.71	60.40	63.17	66.10	65.02	63.17	64.25	66.72	61.33	67.03

The leading Table 5.7, representing the epoch accuracy rate using Inception V3 architecture. Accuracy rate range was 50.85-67.03%. From the first 10 epochs, we got the accuracy is 50.85%. After initiating seventh 10 epochs, we got the highest accuracy rate is 67.03%. Accuracy rate increased by 16.18% after conducting from 1st 10 epochs to 7th 10 epochs.

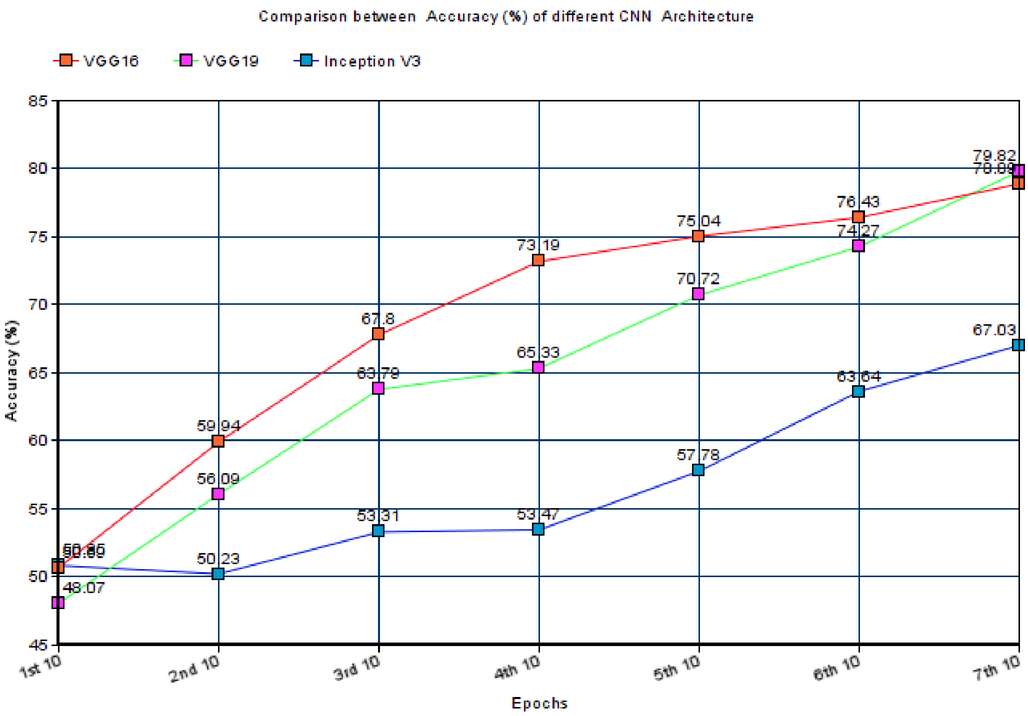

Figure 5.4: Epoch Accuracy Graph

The Figure 5.4 shows Epoch Accuracy with respect to Epochs number where VGG19 is the best and VGG16 is second best performed architecture compare to Inception architecture.

Table 5.8: Testing Accuracy and Loss Function Table

Epoch	Testing Accuracy in Percentage			Loss Function in Percentage		
	VGG16	VGG19	Inception V3	VGG16	VGG19	Inception V3
1st 10	50.23	38.85	52.05	115.18	119.11	114.55
2nd 10	60.85	50.83	56.75	94.05	106.36	110.22
3rd 10	66.77	58.42	52.96	75.83	96.06	111.06
4th 10	77.24	72.69	50.08	55.17	67.87	113.97
5th 10	83.31	78.45	65.55	43.07	54.40	79.70
6th 10	79.51	84.67	72.23	50.58	40.60	66.97
7th 10	93.63	92.72	77.70	19.18	25.06	56.96

The Table 5.8 is exhibiting the comparison between VGG16, VGG19 and Inception V3 architecture of CNN based on Testing accuracy and Loss function. We observe that VGG16 architecture achieves maximum 93.63% validation accuracy and least 19.18% loss function on training data. The testing accuracy and loss function range of VGG16 was 50.23-93.63% and 19.18-115.18% respectively. Later on, VGG19 has achieved very similar testing accuracy with respect to VGG16 which is 92.72% and it provides least Loss function value that is 25.06%. The testing accuracy and loss function range of VGG19 was 38.85-92.72% and 25.06-119.11% respectively. Another architecture Inception V3 obtained validation accuracy is 77.70% and achieved the least loss function is 56.96%. The testing accuracy and loss function range of Inception V3 was 52.05-77.70% and 56.96-114.55% respectively. The Table 5.8 conveys that highest test accuracy have the least test loss and lowest test accuracy contains the highest test loss. From these three architecture VGG16 obtained the highest test accuracy with the lowest error and Inception v3 obtained the lowest test accuracy with the highest error function.

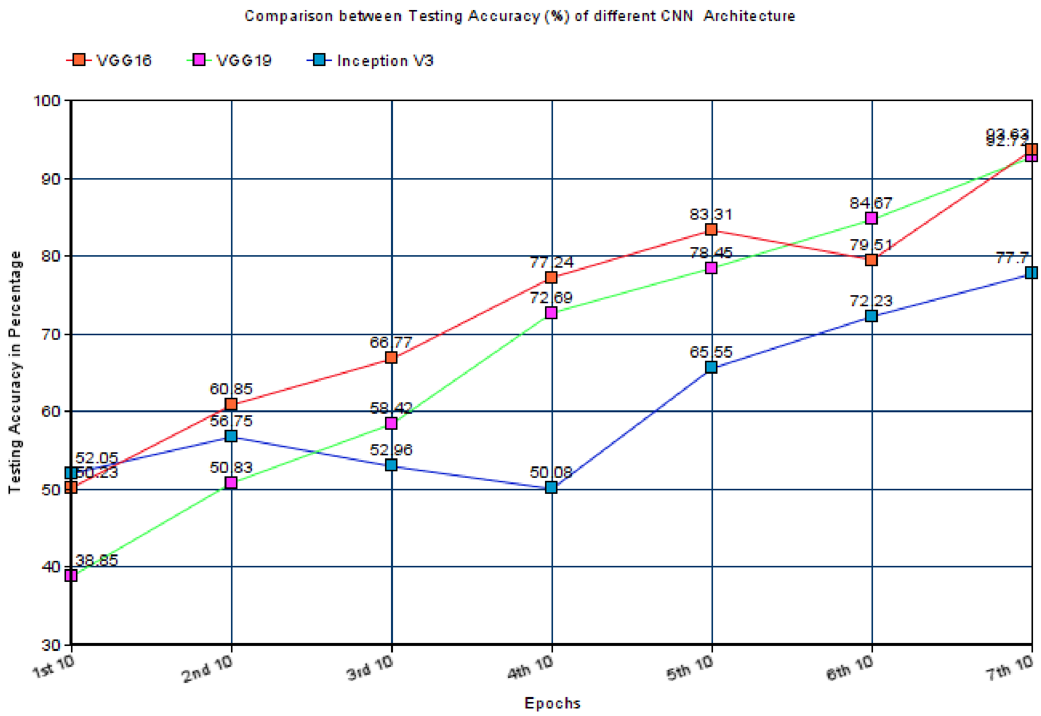

Figure 5.5: Testing Accuracy Graph

The graph on Table 5.5 shows Testing Accuracy with respect to Epochs number where VGG16 outperforms with higher accuracy and second higher accuracy obtained by VGG19 compare to Inception architecture.

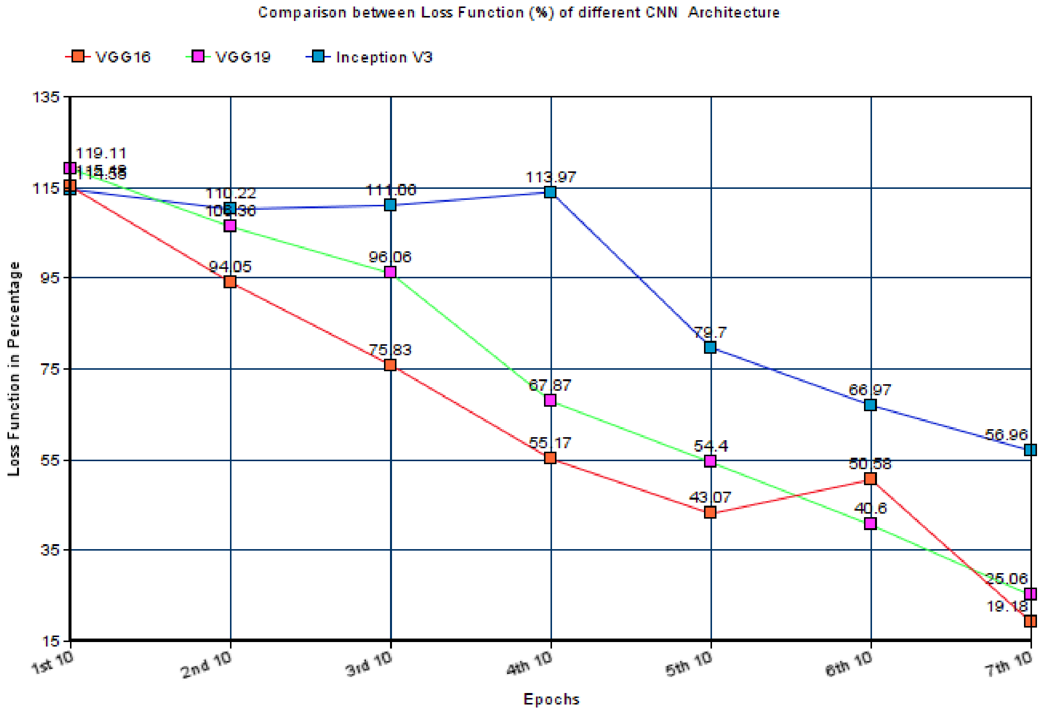

Figure 5.6: Loss Function Graph

The graph shows on Table 5.6, displays Loss Function with respect to Epochs number where VGG16 gives minimum loss function value and Inception gives maximum value of loss function compare to other architecture. As we know, lower error on the dataset means the lowest test loss and highest testing accuracy. Thus, VGG19 produced the highest accuracy with the lowest test loss function.

5.3 Four position classification

Table 5.9: VGG16 Epoch Accuracy Table

Epoch	Accuracy in Percentage									
1st 10	34.42	32.38	37.88	43.18	46.44	46.44	44.81	43.58	55.60	58.66
2nd 10	50.92	38.09	50.71	61.30	42.77	60.49	53.77	51.32	59.47	57.84
3rd 10	66.60	65.58	54.99	60.49	71.69	73.73	81.06	73.73	71.49	77.19
4th 10	70.67	75.56	73.73	76.17	83.91	77.60	79.84	83.71	74.75	82.89
5th 10	88.59	85.13	86.35	85.34	88.80	84.32	86.56	91.24	88.80	87.98
6th 10	83.91	81.85	81.24	93.69	91.04	89.41	95.11	90.84	87.37	90.63
7th 10	82.87	84.30	96.33	95.52	84.52	95.52	95.32	95.11	93.89	97.35

The epoch accuracy Table 5.9 indicates the value of VGG16 architecture. The range of the values from the first epoch to the seventh have a range of 34.42-97.35. Therefore, it clearly identifies the rise of the accuracy after each epoch. VGG16 architecture showed the best result among the three architectures. The highest epoch accuracy was found in this model.

Table 5.10: VGG19 Epoch Accuracy Table

Epoch	Accuracy in Percentage									
1st 10	33.06	42.62	45.11	40.54	56.55	56.13	64.03	65.70	61.95	71.73
2nd 10	70.69	75.26	82.12	84.41	60.29	84.20	81.91	84.20	90.23	88.77
3rd 10	87.11	87.94	76.72	86.69	92.72	92.93	90.02	91.27	92.10	92.93
4th 10	85.86	92.72	96.47	95.01	96.67	92.72	91.68	96.26	94.59	94.59
5th 10	94.18	98.34	96.26	97.51	97.71	98.13	96.47	96.47	96.67	97.30
6th 10	93.35	96.47	97.92	96.26	98.75	85.24	92.31	96.47	96.05	96.67
7th 10	97.51	96.67	95.63	97.71	96.05	96.88	98.54	97.30	98.13	90.85

Table 5.10 shows the value that was obtained by the VGG19 architecture. While applying this architecture the range of the value of accuracy from first to seventh epoch was 71.73-98.54. This architecture also rose the values from each epoch. The accuracy level increased by 21.2.

Table 5.11: Inception V3 Epoch Accuracy Table

Epoch	Accuracy in Percentage									
1st 10	28.51	37.88	39.97	40.73	33.20	43.18	43.58	49.90	50.10	40.12
2nd 10	49.69	43.58	51.32	45.21	44.40	51.12	42.97	53.56	45.21	52.34
3rd 10	54.38	58.25	56.62	53.56	51.30	53.56	61.91	49.90	57.03	53.77
4th 10	53.77	58.04	47.05	51.93	50.92	53.16	49.49	49.49	49.29	49.69
5th 10	50.51	63.14	57.03	55.80	57.43	62.53	56.01	61.71	55.19	58.66
6th 10	61.91	66.40	68.43	67.01	56.80	68.02	70.06	62.73	71.89	74.95
7th 10	76.78	76.58	68.43	75.97	74.95	75.56	80.86	80.45	81.26	72.91

This Table 5.11 presents the values of inceptionV3 architecture. The inceptionV3 architecture shows the result just as the vgg16 and vgg19 models. However, inceptionV3 architecture could not find the accuracy very well. The range of the accuracy using this model was 50.10-81.26. In spite of giving lower accuracy compare to others architectures epoch accuracy, step by step the epoch accuracy is produced increasing value per epoch

Table 5.12: Epoch Accuracy Table

Epoch	Epoch Accuracy in Percentage		
	VGG 16	VGG 19	Inception V3
1st 10	58.66	71.73	50.10
2nd 10	61.30	90.23	52.34
3rd 10	81.06	92.93	61.91
4th 10	83.91	96.67	58.04
5th 10	91.24	98.34	63.14
6th 10	95.11	98.75	74.95
7th 10	97.35	98.54	81.26

This Table 5.12 was created to show the highest value of each epoch. Each epoch had a highest accuracy value. Those highest values were inserted in Table 5.12 to have a clear view of the whole result altogether. As we can see, the vgg19 had the best accuracy among the three architecture with a range of 71.73 to 98.54. The vgg16 had the second-best accuracy range of 58.66 to 97.35. The inceptionV3 was the lowest among these three. It had a range of 50.10 to 81.26.

Table 5.13: Testing Accuracy Table

Epoch	Testing Accuracy in Percentage		
	VGG 16	VGG 19	Inception V3
1st 10	48.43	71.72	40.45
2nd 10	58.09	88.77	52.48
3rd 10	76.76	92.93	48.96
4th 10	79.87	94.59	52.90
5th 10	85.47	97.29	60.58
6th 10	91.90	96.67	79.66
7th 10	95.64	90.85	76.97

This Table 5.13 shows the testing accuracy of all the architectures. These are the final testing accuracy after each epoch. The testing accuracy of vgg16 architecture started from 48.43%. After the first epoch, the accuracy went up gradually. Finally, the result increased significantly in the last epoch. At the end of the last epoch, finally the value of testing accuracy rose to 95.64%. Similar patterns can be found when looked at the other two model as well. The VGG19 has a range of 71.72-90.85% . And the InceptionV3 has a testing accuracy result from 40.45 to 76.97%.

Table 5.14: Loss Function Table

Epoch	Loss Function in Percentage		
	VGG 16	VGG 19	Inception V3
1st 10	119.09	72.28	154.68
2nd 10	94.59	26.04	109.42
3rd 10	59.11	18.41	121.68
4th 10	48.15	14.80	110.90
5th 10	36.10	07.43	103.73
6th 10	22.03	08.68	54.29
7th 10	14.76	21.24	57.94

The loss function of all the architectures are shown in this Table 5.14. These are the final loss function after the finishing of each epoch. As we can see that the loss function generated from these architectures are quite high at the beginning. The loss function decreases after each epoch. Loss function range of vgg16 architecture was 119.09-14.76. The loss function percentage went low rapidly. Almost similar case happened again in inceptionV3, where the range was from 154.68% to 57.94%. The vgg19 model was quite subtle as the range was from 72.28-21.24%.

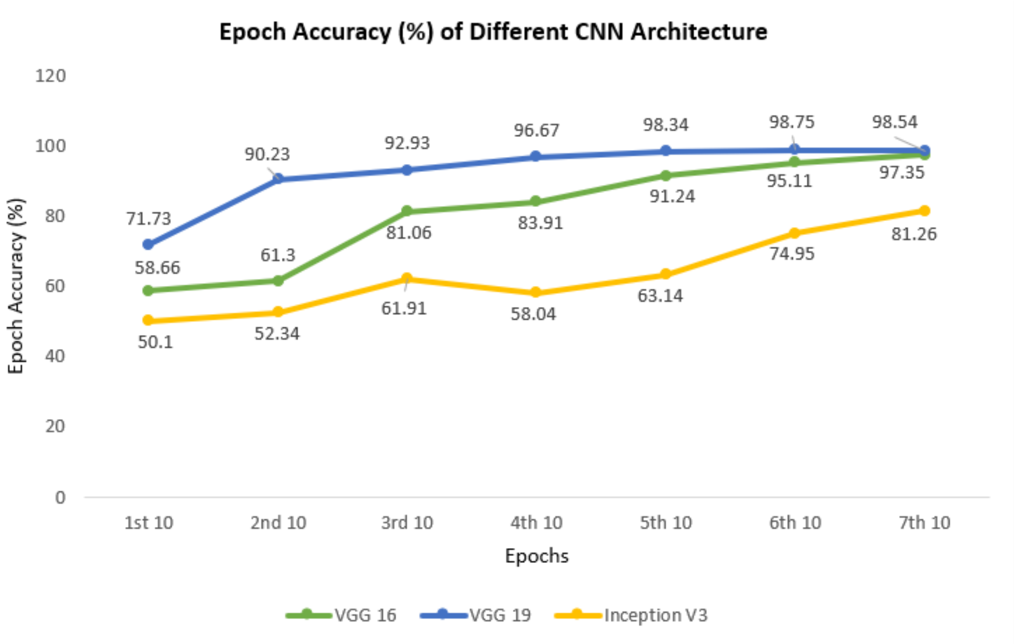

Figure 5.7: Graph of Epoch Accuracy

The graph on Figure 5.7 was used created to show the highest epoch accuracy of per epoch. As the highest epoch accuracy was taken, almost all the time the line is rising. In the inception line the fourth epoch went down but then again it started to rise. If we see the highest epoch accuracy among the three architecture models, we can see that the vgg19 is the one with the highest value.

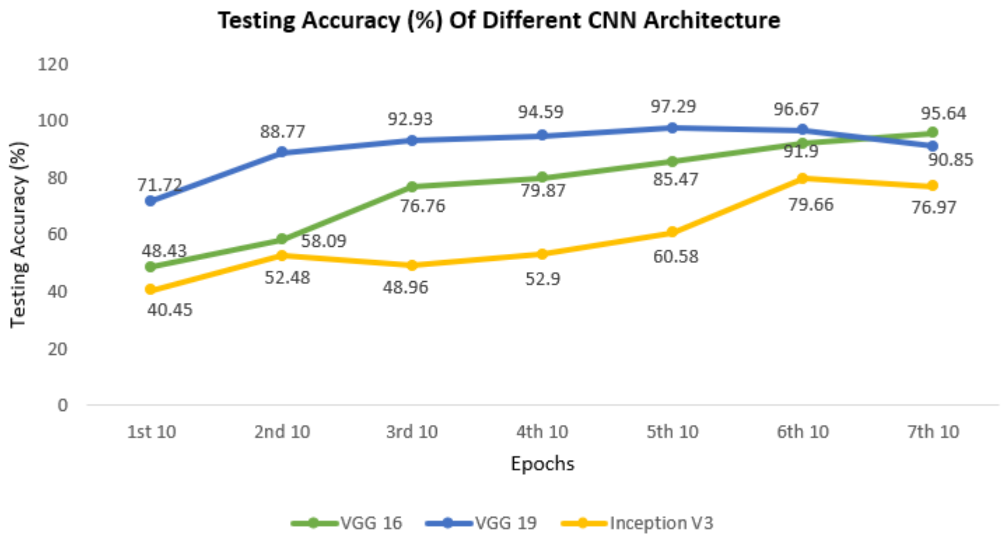

Figure 5.8: Graph for Testing Accuracy

This graph in Figure 5.8 shows the testing accuracy of 7 epochs. The VGG19 line gradually increased from the first epoch to fifth epoch. Then it went down at the sixth and seventh epoch. On the other hand, the VGG16 gradually went up and reached 95.5%, the highest value among the three models. The yellow line that shows the inception graph fluctuated several times.

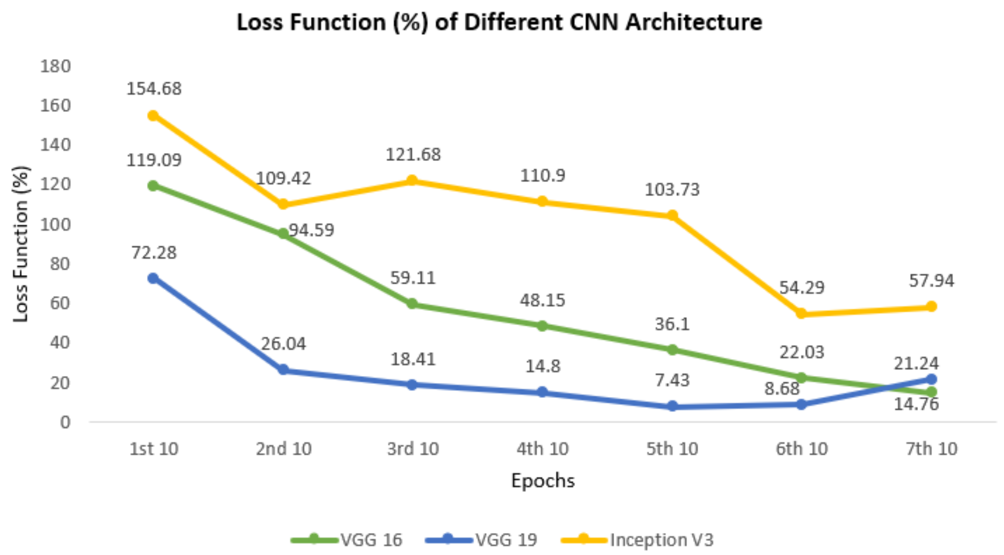

Figure 5.9: Graph for Loss Function

The graph in Figure 5.9 indicates the loss function. Generally, the loss function of the epoch gradually decreases. As we can see in the VGG16 line, the line went down and then gradually went up. However, it decreased a lot in the end. Same goes for the VGG19 and inception architecture. In these architectures, we can see that vgg16 has the lowest lost function among the three models.

Table 5.15: Comparison between Epoch accuracy of different classification

Epochs	Binary Classification			Five Class Classification with Four Brain Lobe			Four Position Classification		
	VGG16 Accuracy (%)	VGG19 Accuracy (%)	InceptionV3 Accuracy (%)	VGG16 Accuracy (%)	VGG19 Accuracy (%)	InceptionV3 Accuracy (%)	VGG16 Accuracy (%)	VGG19 Accuracy (%)	InceptionV3 Accuracy (%)
1	81.91	79.32	71.57	50.69	48.07	50.85	58.66	71.73	50.10
3	82.55	82.55	83.52	67.80	63.79	53.31	81.06	92.93	61.91
5	88.13	85.32	94.51	75.04	70.72	57.78	91.11	98.34	63.14
10	93.13	90.15	91.52	78.89	79.82	67.03	97.35	98.54	81.26

The Table 5.15 representing the comparison of three types classification namely Binary Classification, Five Class Classification with Four Brain Lobe and Four Position Classification based on three architecture of CNN. Here, we took four epochs rather than ten epochs accuracy of VGG16, VGG19 and inception V3 that helps us to study the accuracy scheme very easily and understanding the architecture accuracy flow step by step whether its increasing or decreasing when moved on one epoch to another epoch. In Binary classification, VGG16 gives the highest accuracy compare to VGG19 and Inception V3 which is 93.13%. Using Vgg19, Five Class Classification obtains the best accuracy compare to VGG16 and inception V3. Another classification that is Four Position Classification achieves highest accuracy Vgg19 architecture. From these three classifications, Five Class Classification accords the highest accuracy compare to Binary Classification and Five Class Classification with Four Brain Lobe. The accuracy rate for Four Position Classification is 97.35%.
VGG16:

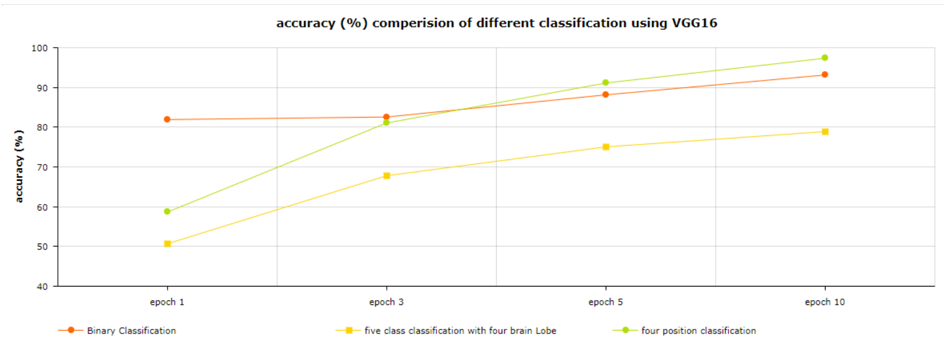

Figure 5.10: Comparison between different classification using VGG16

Adopting VGG16, From the Table 5.10, we can see that initially four class classification produced the average accuracy and end of the iteration it comes up with the highest epoch accuracy; in the other hand, binary classification starts with the highest epoch accuracy and end up average accuracy while five class classification accords least start up accuracy and finally able to make lowest accuracy compare to basic CNN architecture of VGG19 and Inception V3.

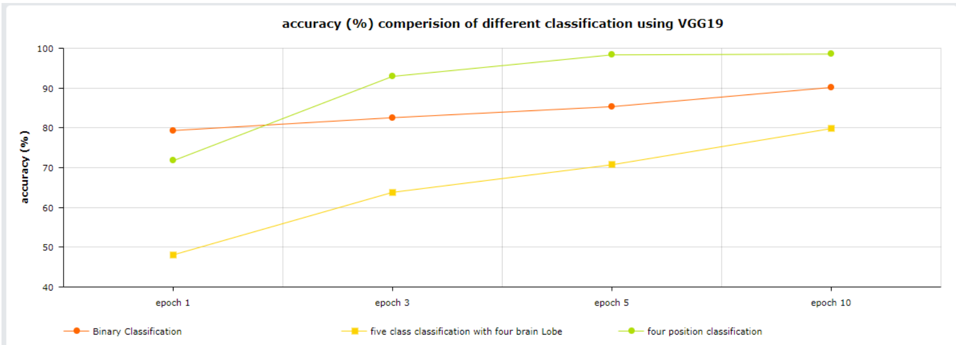

Figure 5.11: Comparison between different classification using VGG19

The graph on Figure 5.11 showing comparison between different architecture using VGG19 and giving the evidence that Five class classification with four Brain Lobe assembled the least accuracy form the starting epoch accuracy to end of the epoch accuracy. Like VGG16, binary classification scored best accuracy initially and scored average accuracy at the end of result. Again, in the same way the four-position classification accords best accuracy in the end compare to other architectures accuracy.

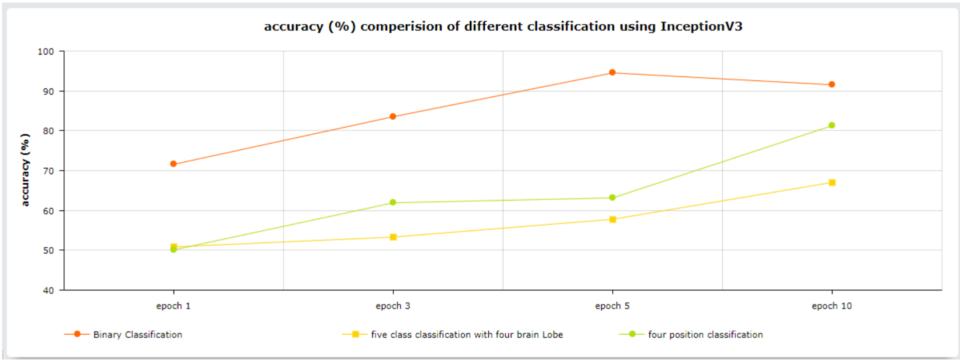

Figure 5.12: Comparison between different classification using InceptionV3

In Figure 5.12, While using inception V3, dramatically Binary classification reached the highest initial value which is 71.57% and accord the highest accuracy rate is 91.52%. Additionally, four class position classification and five class classification begin with average accuracy, after a while four classification obtain average accuracy, and five class classification accord least accuracy.
After experimenting and monitoring the Table 5.15 and 5.8, graph and result of three classifications with VGG16, VGG19 and Inception V3, we are capable of coming to a perfection that "Five class classification with four brain Lobe" secured lowest epoch accuracy which is 79.82%, and least testing accuracy with a higher loss function. In addition, the Table 5.15 and Figure 5.9 shows that "Four Position" classification accords the best Epoch accuracy using VGG19 and the epoch accuracy rate is 98.54% with loss function is .2124. Besides "Binary" classification obtains the highest testing Accuracy which is 98.68 and least error which is 0.0528 using VGG19 architecture showed in Figure 5.2 and 5.3. Finally, the noticeable thing is Binary classification and four class classification accorded highest accuracy, and five class classification gives a nearly highest accuracy using VGG19. Thus, we can say that VGG19 is the best architecture of CNN compare to others for acquiring better performance and accuracy.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

To sum up, in this work we have presented CNN system with fMRI data. This proposed work has helped us to find the different level of accuracy using different architectures such as VGG16, VGG19, InceptionV3 by three classifications binary classification, five Class Brain Lobe Classification,4 position classification. By using these architectures, we can easily compare in between as each of them produce different level of output. Our main goal is to make a system that can easily achievable by every visually impaired people. Implement such software that can show better accuracy to find more stable data set. Moreover, we can say that binary classification has a higher accuracy as it has less loss function. The VGG19 is a good architecture as it generates higher level of accuracy. To conclude, we are working to help those people who suffer from brain tumor we want to help them by taking proper treatment at early stage. The motivation behind these strategies is to make a fundamental judgment about detecting tumors and their implementation. In future, we are planning to use some algorithms along with CNN that can generate a higher accuracy.

6.2 Future Plans

In future, we are planning to use some automated tumor detection algorithms that can detect more lesions need to be implemented in our method so that we can deal with complex cases. We will ensure high regulation structure in fMRI on different tumor tissues. Moreover, we are planning to use some algorithms along with CNN that can generate a higher accuracy. In addition, we want to use some more architecture and more classification that can produce more variation in comparison.

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