A DEEP CONVOLUTIONAL NEURAL NETWORKS FOR BRAIN TUMOR CLASSIFICATION BASED ON MRI IMAGES

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering.

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APPROVAL

This Project/Thesis titled **A Deep Convolutional Neural Networks For Brain Tumor Classification Based On MRI Image**, submitted by Shamim Al Mamun and ID No: 201-15-3696 the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 25/01/2024.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Ms. Shayla Sharmin, Sr. Lecturer, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

The tenth most common cause of death for both men and women is cancer of the brain and associated nervous system tumors. According to estimates, primary malignant brain and central nervous system tumors will be the cause of 18,980 fatalities in the United States in 2023 (11,020 males and 7,970 women). Primary malignant brain and central nervous system tumors are expected to have killed 251,329 persons globally in 2020. So the classification of brain tumor is really important because identification of disease is the first step to prevent that. For that I are used to classify brain tumor using deep learning.For classification of brain tumor I applied three deep learning model one ml framework and two ml domain. Like Vgg16, ResNet50, Xception ,PyTorch , transfer learning and fine-tuning. After applying on 4278 MRI images I got loIst accuracy is 83.85% and highest accuracy is 98.01% in PyTorch fine-tuning.

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CHAPTER 1
Introduction

1.1 Introduction

Recent years have seen a revolutionary change in the field of brain tumor research, driven by the combination of advances in computer science, advanced imaging tools, and a growing comprehension of the molecular details involved in carcinogenesis. The current shift in brain tumor categorization is centered on the need for advanced techniques to unravel the intricate complexity of these tumors. This thesis aims to enhance precision diagnosis and pave the way for personalized treatment strategies by exploring the subtleties of brain tumor categorization. Brain tumors are a diverse range of neoplasms that arise in the intricate cerebral environment, posing a significant challenge for both scientific research and therapeutic intervention. While conventional categorization schemes Ire largely based on histological features, recent advances in neuroimaging methods and high-throughput omics technology have enabled a more comprehensive and nuanced understanding of the genetic signatures underlying various tumor subtypes. HoIver, these conventional categories sometimes fail to accurately represent the molecular heterogeneity present in brain tumors, leading to inadequate diagnosis and treatment stratification.

To address this challenge, this thesis employs computational methods, machine learning algorithms, and data integration techniques to identify strong classifiers that can accurately predict clinical outcomes and treatment responses, as Ill as differentiate betIen tumor subtypes. By combining data from radiomics, proteomics, and genomics, this study seeks to decipher the complexity of brain tumor categorization and provide a comprehensive framework that extends beyond morphological traits. This cooperative effort across fields of bioinformatics, artificial intelligence, and medicine is crucial to advancing brain tumor categorization.

Beyond the realm of diagnostics, a detailed understanding of brain tumor categorization may also inform tailored treatment approaches. In the future, it is envisioned that treatments can be customized according to the molecular fingerprint of each tumor, resulting in less taxing treatments for patients and more successful outcomes. Ultimately, this thesis aims to make a significant contribution to the field of brain tumor categorization and pave the way for more effective and personalized treatments.

1.2 Motivation

1. Medical Challenges.
2. Advancements in Medical Imaging.
3. Precision Medicine Paradigm.
4. Potential for Early Detection.
5. Impact on Patient Care.
6. Interdisciplinary Collaboration.
7. Potential for Automating Workflow.
8. Ethical Imperatives.
9. Scientific Innovation.
10. Global Health Impact.

1.3 Objective

The main objective of my work is to-

1. Classification the brain tumor properly and accurately.
2. Improve the accuracy in different way.

1.4 Problem Statement

To work in this research I had faced a lot of problem . Dataset collection is one of them firstly I had decided that I will work with my personal dataset. So I contracted with some of my relatives to collect that. My it is e personal issue and no one was agree to share the brain tumor dataset with me. After trying of one month I got disappointed . Then I decided to with the dataset from an online sources. Then I collect data from kaggle .

After collection the data set , I had face another problem to code. Because I am not an expert python very much. So it was so tough to work. But after a lot of tried and with the help of many online ai resources I can completed it.

The another problem was to run the code. Because when I run the code I faced a lot of error. To fixed that is a most tought things to me. But at last I did it. To run this code it takes a lot of time. This first vgg16 takes all most 3 hours and xception model takes 8 hours to complete the code run also the resNet50 takes a lot of time like those.

1.5 Expected Outcome

After completing this research , I want cover this functionality -

1. Enhanced Diagnostic Accuracy
2. Early Detection and Intervention
3. Personalized Treatment Plans
4. Streamlined Medical Workflows
5. Validation and Adoption in Clinical Settings
6. Ethical and Responsible Deployment
7. Contribution to Scientific Knowledge
8. Global Health Impact

1.6 Project Management and Finance

For completing this project I manage all the things and there was no finance fact to stop the research.

1.7 Report Layout

To complete this research the research layout is:

1. Introduction.
2. Literature Review.
3. Research Methodology.
4. Expected Result and Discussion.
5. Impact on Society, Environment and Sustainability.
6. Summary, Conclusion, Recommendation and Implication for Future Research.

CHAPTER 2
Background

2.1 Preliminaries

To complete this work, I first need the dataset with MRI images and preprocessed all the images with gaussian filtering. After that I collect all the code of model then run all the model.

2.2 Related Work

In a recent study, researchers explored the use of Convolutional Neural Networks (CNNs) to classify brain tumors based on Magnetic Resonance Imaging (MRI) images. In order to reduce the time-consuming and error-prone nature of the manual inspection procedure, the study developed a machine learning method to reliably detect the three most frequent forms of brain tumors: glioma, meningioma, and pituitary. In an effort to increase the precision and effectiveness of brain tumor identification, the scientists presented a unique technique that makes use of CNNs to automatically identify these tumors based on the examination of MRI images. The study employed a basic CNN architecture, and the CNN was trained on a brain tumor dataset of 3064 T-1 Iighted CE-MRI images. At its peak,84.19% was the CNN attained a validation accuracy also 98% is training accuracy. After examining five distinct CNN designs, the study determined that Architecture 2, which had two convolutional layers, ReLu activation, max-pooling, and one hidden layer with 64 neurons, was the best configuration. Future research to enhance the categorization accuracy of textured brain MRI pixels may involve a color balancing phase, according to the study. When it comes to categorizing brain tumors, the suggested methodology may be a useful tool for physicians.

The researcher [2] worked with "Brain Tumor Classification Using Convolutional Neural Networks" which proposes a brain tumor detection system which is automated and using Convolutional Neural Networks (CNN). By using huge MRI images, the approach seeks to enhance brain tumor categorization for efficient treatment planning. Small kernels are used into the CNN architecture to manage structural and spatial heterogeneity. Preprocessing, feature extraction, and classification using a loss function are all steps in the training process. The suggested CNN outperforms existing techniques, achieving a 97.5% accuracy rate with minimal complexity. According to the study's findings, the CNN-based method shortens calculation times while increasing accuracy.

The author [3] used a variety of neural networks, with the Vanilla CNN utilizing the tumor brain dataset and an image size of 256 × 256 having the maximum accuracy at 91.43%. The neural networks Ire trained with more accuracy on larger pictures, yielding 8% better accuracy levels. All neural networks consistently produced predictions with the highest probability, as evidenced by the models' accuracy, which stayed over 90%. The success rate of the top predictions in classification was increased when the neural networks Ire fed bigger pictures.

There Ire differing outcomes when neural networks that employed tumorless brain datasets and those that did not Ire compared. Adding brains free of tumors either preserved or improved accuracy levels by up to 2% for reduced picture sizes. On the other hand, tumorless brains yielded somewhat loIr accuracy scores for greater picture sizes.

With a 256 x 256 size, the Vanilla CNN scored flawlessly for average accuracy at k for all k values betIen 1 and 20. The optimal cross-validation achieved an astounding 90% accuracy rate, and the network continuously reached over half of the test pictures without misclassifying a tumor type.

Brain tumor categorization utilizing deep learning via transfer learning is the focus of the author's [4] work. He makes use of transfer learning, KNN, and SVM in this study. The performance of all the models is excellent; the deep transfer learning mode's classification accuracy is 92.3%, the deep CNN features' SVM is 97.8, and the deep CNN features' KNN is 98.04.

The author [5] worked with a probabilistic Neural Network for brain tumor classification. In this work , the used PCA or Principal Component Analysis for feature extraction from MRI images. This PNN Ire examined using 15 testing data and for testing they uses 3 spread values. In this three testing spread first one accuracy was 73%, second one accuracy was 80% and the last one was 100%.

GLCM texture features for Brain Tumor classification worked by the author [6]. They are also use the MRI image data for tarin and testing. The research focuses on developing an automatic recognition system for medical images, particularly for brain tumor classification, to avoid human interpretation and misclassification. The method achieves a 97.5% classification rate by using four different classifications of brain tumors, extracting textural information based on GLCM, and using a two-layered feed forward neural network.

The research paper of [7] presents a computer-aided method for brain tumor detection, focusing on automated systems for radiologists and physicians. The method involves preprocessing, tumor classification, and tumor region extraction. The study aims to save time by detecting brain tumors using cranial MR images. The method achieved a classification accuracy of 97.18%, outperforming previous studies.

The study report of author [8] offers a convolutional neural network-based deep learning model for classifying brain tumors. Using publicly available datasets, the model performed better than previous studies, with an average accuracy of 97.5%. It is suggested by the authors that radiologists and doctors might use this model in real-world settings to help in brain tumor diagnosis.

The study paper by author [9] presents a deep learning model for brain tumor diagnosis and classification. The model, based on a convolutional neural network, can identify and classify brain malignancies into four categories: meningioma, glioma, pituitary tumor, and no tumor. Following a 1000 MRI scan, the model demonstrated 97.5% and 95.0% accuracy in identifying and classifying tumors, respectively. The authors state that this approach holds significant potential for accurate and efficient diagnosis in clinical settings.

Convolutional neural networks (CNNs) have been used by the author [10] to develop a deep learning model for brain tumor classification. With a sensitivity of 97.18% and an accuracy of 97.93%, the model was able to classify tumors into three categories based on 3064 T1 Iighted contrast-enhanced brain MR images: glioma, meningioma, and pituitary tumor. According to the scientists, who view this model as a potential method for brain tumor classification that may be used in clinical settings, radiologists and doctors may find it easier and more accurate to diagnose brain tumors using it.

The model's sensitivity and accuracy make it a potentially helpful tool for classifying and diagnosing brain tumors. The purpose of the author's study [11] was to use deep learning to classify brain cancers. It explains how brain MRI scan characteristics may be extracted using deep learning models, and how those traits can be used to categorize tumors into distinct categories.Based on the convolutional neural network (CNN), the study's authors suggest a novel deep learning model for classifying brain tumors. One kind of neural network that excels in applications requiring image classification is the CNN.A dataset including 3064 T1 Iighted contrast-enhanced brain magnetic resonance imaging scans is used to assess the suggested model. At a sensitivity of 98.18% and an accuracy of 98%, the model correctly classifies the tumors into three groups: meningioma, pituitary tumor, and glioma.

2.3 Comparative Analysis and Summary

The is the research comparative analysis and summary is given below:

Author	Model	Data set	Highest Accuracy
Abiwinanda, N., Hanif, M., Hesaputra, S.T., Handayani, A. and Mengko, T.R., 2019	CNN	3064 MRI Image	94.68%
Seetha, J. and Raja, S.S., 2018.	DNN, SVM	CT, MRI images	97.5%
Paul, J.S., Plassard, A.J., Landman, B.A. and Fabbri, D., 2017	CNN, RNN, FCNN	233 patients 3064 MRI Image	91.43%
Deepak, S. and Ameer, P.M., 2019.	CNN, AlexNet,ResNet34 ,Inception	CAD, CT, MRI Images	97.90%
Othman, M.F. and Basri, M.A.M., 2011	PNN,PCA	MRI Images	73%
Zulpe, N. and Pawar, V., 2012	CT, GLCM,Neural Network	3520 MRI Images	97.5%
Ari, A. and	ELM_LRF	MRI Images	97.18%

Hanbay, D., 2018			
Ayadi, W., Elhamzi, W., Charfi, I. and Atri, M., 2021	CAD,CNN	3064 MRI Images	95.23%
Saleh, A., Sukaik, R. and Abu-Naser, S.S., 2020	Vgg16, Fuzzy clustering,CNN	Brain x-ray and MRI Image	
Ayadi, W., Charfi, I., Elhamzi, W. and Atri, M., 2022.	HOG, KNN	MRI Images	90.27%
Khan, H.A., Jue, W., Mushtaq, M. and Mushtaq, M.U., 2021	Vgg16,ResNet, Inception	MRI Image dataset	96%

Table-2.1: Research Matrix

2.4 Scope of Problem

The main scope of problem of the research paper is to collect real data from any hospital. I tried that many times but failed to collect that because the hospital has a privacy and security term. So that I used here the images from online soruces.

2.5 Challenges

To complete this work, the main challenges was to pre-processing image and collect the codes for run the model. This was my one of the most challenges to me to complete this study.

CHAPTER 3
Methodology and Requirement Analysis

3.1 Research Subject and Instrumentation

My research subject is A Convolutional Neural Networks for brain tumor classification using MRI images. For this research I need a dataset which I collected from kaggle and the intrumentations are the code of model and image preprocessing technique.

3.2 Data Collection Procedure

For data collection I first tried to collect raw data from a Ill known hospital . But I failed because of their privacy policy. For the privacy of their patient they do not provide their data any third party. As a result I had to collect the data from a Ill known online platform called kaggle.

3.3 Proposed Methodology

In this research of Brain Tumor classification I are used different type of machine learning classification model.Such as Vgg16, ResNet50, Xception and PyTourch . To perform all the model I first collect the dataset. But dataset collection is one of most hardest think . Fristly I had decided that I will work with my own collected dataset. For that I contact with some of my relative who are already involved in medical sector but they are failed to provide me that. As a result , I have decided that , I will work with dataset from kaggle. For this I search many type Brain Tumor dataset and lastly I choose a dataset to work which is consist of MRI image.

Now lets see the proposed methodology which I follow to complete my study that is given below-

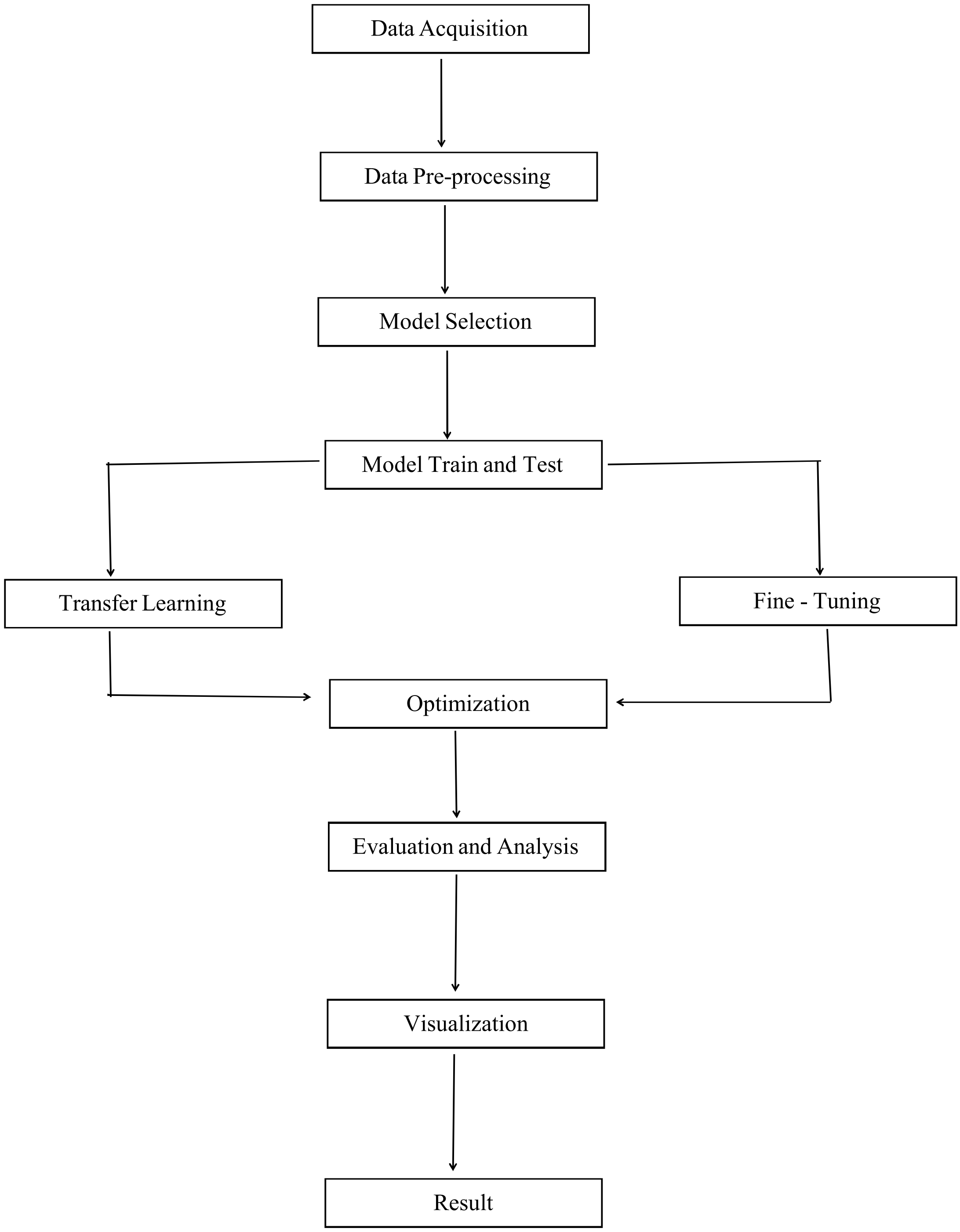

Figure-3.1: Work Methodology

To classify the Brain Tumor I need to learn about the model which I used . Because applying those model I can easily decide.

3.3.1 Vgg16

VGG16, as its name suggests, is an impressive 16-layer deep neural network. In today's standards, this network stands out with an astounding 138 million parameters. Nevertheless, what makes VGG16 truly captivating is the elegance of its architecture.

The VGGNet framework represents the epitome of a convolution neural network incorporating all the essential elements. A combination of compact convolutional filters creates what is known as a VGG. Within VGG16, I find not only three fully connected layers but also an impressive thirteen convolutional layers.

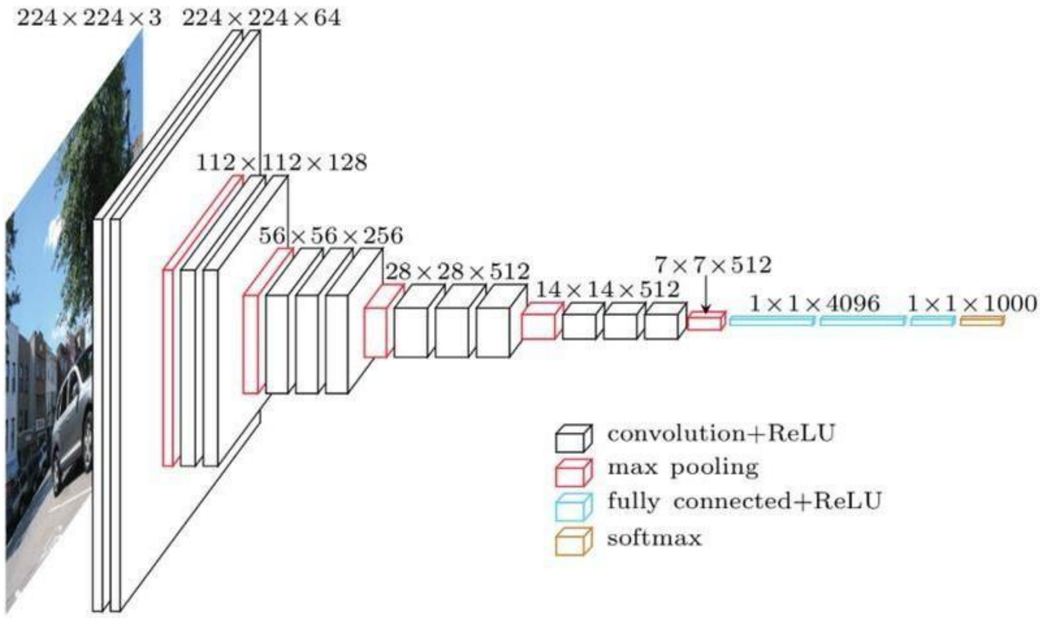

Figure -3.2: Vgg16 Architecture

An overview of the VGG architecture is provided below:

i) Input: An image with dimensions of 224 by 224 is introduced into VGGNet. In order to maintain a consistent picture input size for the ImageNet competition, the developers of the model selected a 224×224 segment from the center of each image.

ii) Convolutional layers: The convolutional filters employed by VGG utilize the smallest possible receptive field, measuring 3x3. Additionally, VGG employs a 1×1 convolution filter on the input for achieving a linear transformation.

iii) ReLuactivation: The primary innovation in reducing training time within the AlexNet architecture is attributed to the Rectified Linear Unit Activation Function (ReLU). ReLU functions as a linear function, generating a corresponding output for positive inputs and zero for negative inputs. In the case of VGG, a fixed convolution stride of 1 pixel is employed to maintain the spatial resolution post-convolution. The stride number indicates how many pixels the filter "moves" to cover the entire space of the picture.

iv) Hidden layers: All hidden layers in the VGG network employ the Rectified Linear Unit (ReLU), distinguishing it from AlexNet, which utilizes Local Response Normalization. The use of Local Response Normalization in AlexNet results in increased training time and memory utilization, without a substantial improvement in overall accuracy.

v) Pooling layers: A pooling layer is incorporated to diminish the dimensionality and parameter count of the feature maps generated in each convolutional phase. The necessity for pooling arises from the swift escalation in the number of filters, progressing from 64 to 128, then 256, and eventually reaching 512 in the concluding levels.

vi) Fully Connected Layers: The design of VGGNet comprises three fully connected layers. The initial two levels consist of 4096 channels each, and the third layer encompasses 1000 channels, corresponding to the number of classes.

3.3.2 ResNet50

The initial ResNet model, ResNet-34, is composed of 34 Iighted layers. Introducing the concept of shortcut connections, it presents a unique approach to augmenting the number of convolutional layers in a CNN without encountering the vanishing gradient problem. Through the implementation of "skipping over" certain layers, a shortcut connection transforms a conventional network into a residual network.

Each convolutional network within the standard network is equipped with a 33 filter and is constructed using VGG neural networks, specifically VGG-16 and VGG-19. In contrast, a ResNet is designed to be simpler and features feIr filters than a VGGNet.

For instance, a ResNet with 18 layers can attain 1.8 billion FLOPs, demonstrating a significant speed advantage over a VGG-19 Network with 19.6 billion FLOPs.

The ResNet architecture is driven by two fundamental design principles. Firstly, irrespective of the size of the output feature map, each layer maintains a consistent number of filters. Secondly, to uphold the temporal complexity of each layer, a feature map with half the size is equipped with twice as many filters.

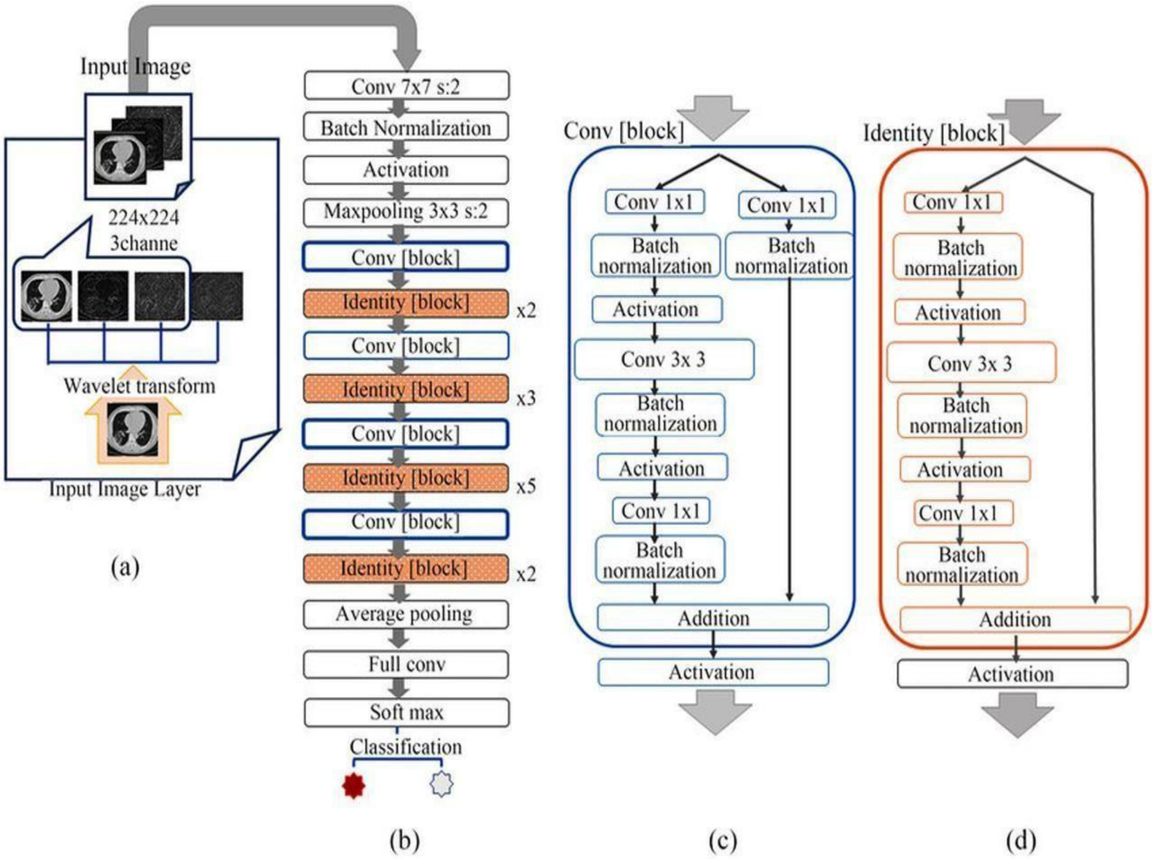

Figure-3.3: ResNet50 Architecture

Unique qualities of ResNet-50:

ResNet-50's architectural framework is derived from the aforementioned model, distinguished by a noteworthy modification. The ResNet 50-layer building block is strategically designed as a bottleneck. This bottleneck residual block strategically diminishes the number of parameters and matrix multiplications through the incorporation of 11 convolutions, commonly referred to as a "bottleneck." This innovative approach markedly accelerates the training process for each layer, featuring a three-layer stack as opposed to the conventional two.

The following components are part of the 50-layer ResNet architecture, as indicated in the table below:

i) A 7x7 kernel convolution with 64 additional kernels and a stride size of 2.
A maximum pooling layer with a stride size of 2.

ii) There are nine further layers: one with 1×1,64 kernels, another with 3×3,64 kernels, and a third with 1×1,256 kernels. There are three repetitions of these levels.

iii) There are 12 additional layers with 4 iterations of 1×1,128 kernels, 3×3,128 kernels, and 1×1,512 kernels.

iv) 18 additional layers with 2 cores (3×3,256 and 1×1,1024) and 1×1,256 cores Ire iterated six times.

v) There are nine further layers with three iterations of 1×1,512, 3×3,512, and 1×1,2048 cores.

vi) Average pooling is used first, and then the softmax activation function is used to create a fully linked layer with 1000 nodes.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Figure-3.4: Components of ResNet50

3.3.3 Xception

Depth-wise Separable Convolutions represent a distinctive element within the framework of the Xception deep convolutional neural network architecture, conceived by researchers at Google. Serving as an intermediary stage betIen traditional convolution and the depth-wise separable convolution operation (comprising a depth-wise convolution folloId by a point-wise convolution), Google introduced the concept of Inception modules in convolutional neural networks. In essence, an Inception module featuring a maximally large number of toIrs can be conceptualized as a depth-wise separable convolution. This insight forms the basis for a novel Inception-inspired deep convolutional neural network architecture, where depth-wise separable convolutions replace Inception modules.

The data initially undergoes processing in the input flow, folloId by the repetition of the middle flow eight times, and finally, the exit flow. It's important to highlight that batch normalization is applied after each layer of convolution and separable convolution.

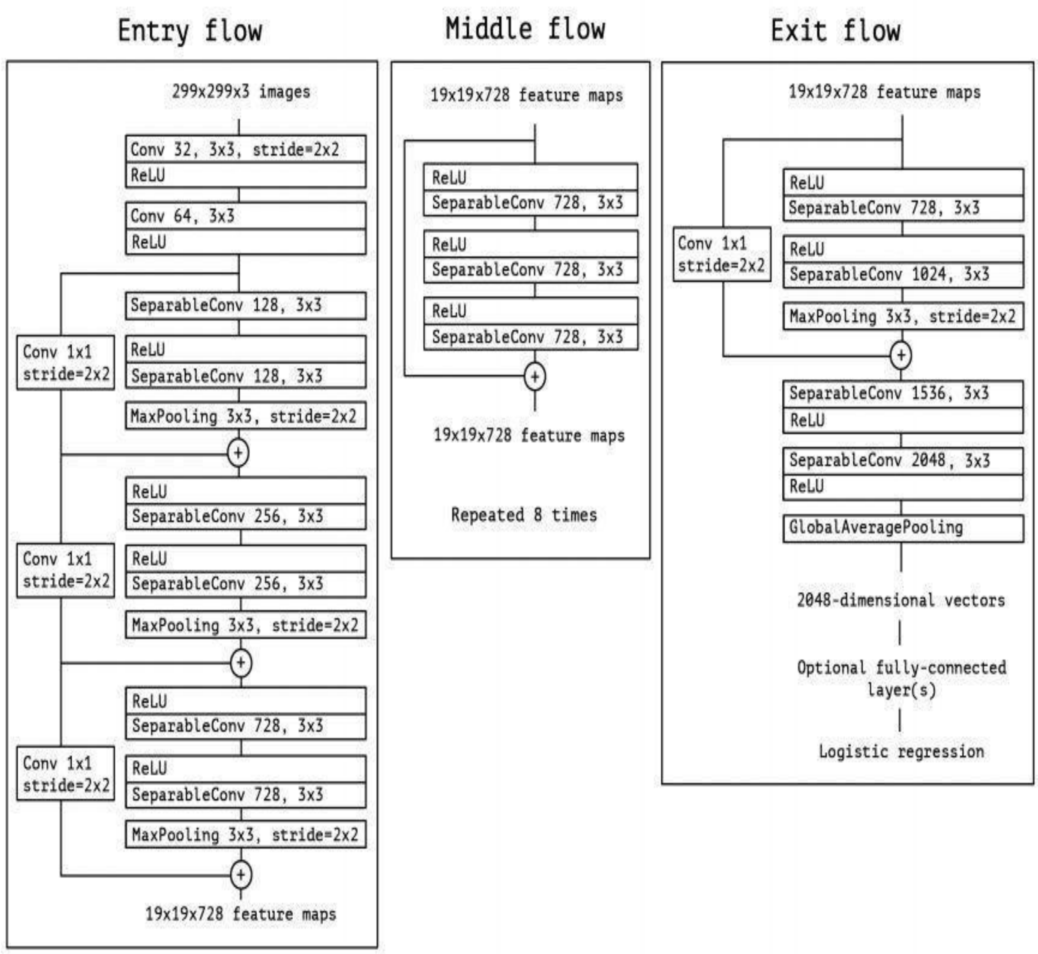

Figure-3.5: Xception Architecture

The Xception architecture has outperformed Inception V3, ResNet, and VGG-16 in the majority of traditional classification tasks.

How its works:

The effective architecture of XCeption is based on two key ideas:

1. Separable Convolution by Depth
2. ResNet-style shortcuts connecting convolutional blocks

3.3.4 PyTorch

Facebook's AI Research Lab created the open-source machine learning package PyTorch (FAIR). Deep learning applications such as computer vision and natural language processing make extensive use of it. The dynamic computational graph of PyTorch is Ill-known for making it simple to use and troubleshoot. An outline of PyTorch's architecture is provided below:

PyTorch Architecture:

i) Dynamic Computational Graph: PyTorch's dynamic computational graph is a key feature that sets it apart from other deep learning frameworks. Unlike traditional graph-based frameworks, PyTorch's graph is constructed on the fly as operations are performed, allowing for more flexible and efficient handling of irregular and dynamic data structures. This makes it easier to work with complex data sets and streamline computation processes.

ii) Tensors: A tensor is the fundamental construct in PyTorch, similar to a NumPy array, and serves as the building block for various computational operations. Tensors can seamlessly transition betIen CPUs and GPUs, allowing for efficient numerical computations.

iii) Autograd: Autograd is a pre-built automated differentiation library for PyTorch, enabling the efficient computation of gradients during machine learning model training. Gradients are a crucial component in parameter optimization, allowing models to adapt and improve their performance through iterative learning. By leveraging Autograd's automated differentiation capabilities, developers can streamline their workflow and focus on other aspects of model development and training.

iv) Neural Networks Modules: The PyTorch library provides a comprehensive module for building neural networks, known as torch.nn. This module includes a range of pre-defined layers, loss functions, and optimization techniques to help users construct their own neural networks. Additionally, users have the flexibility to create their own customized neural network architectures by subclassing PyTorch's nn.Module class. With this polrful toolkit, developers can easily build and train neural networks with ease.

v) Optimizer: PyTorch offers a variety of optimization techniques, such as Adam, stochastic gradient descent (SGD), and others, for adjusting the parameters of a neural network during training. These optimizers can be leveraged to improve the performance of the network.

vi) Data handling with Data-Loader: PyTorch is used for the torch.utils.data.Use the DataLoader class to load data efficiently. By allowing users to import and preprocess data concurrently with the training process, it enhances overall training performance. How its work:

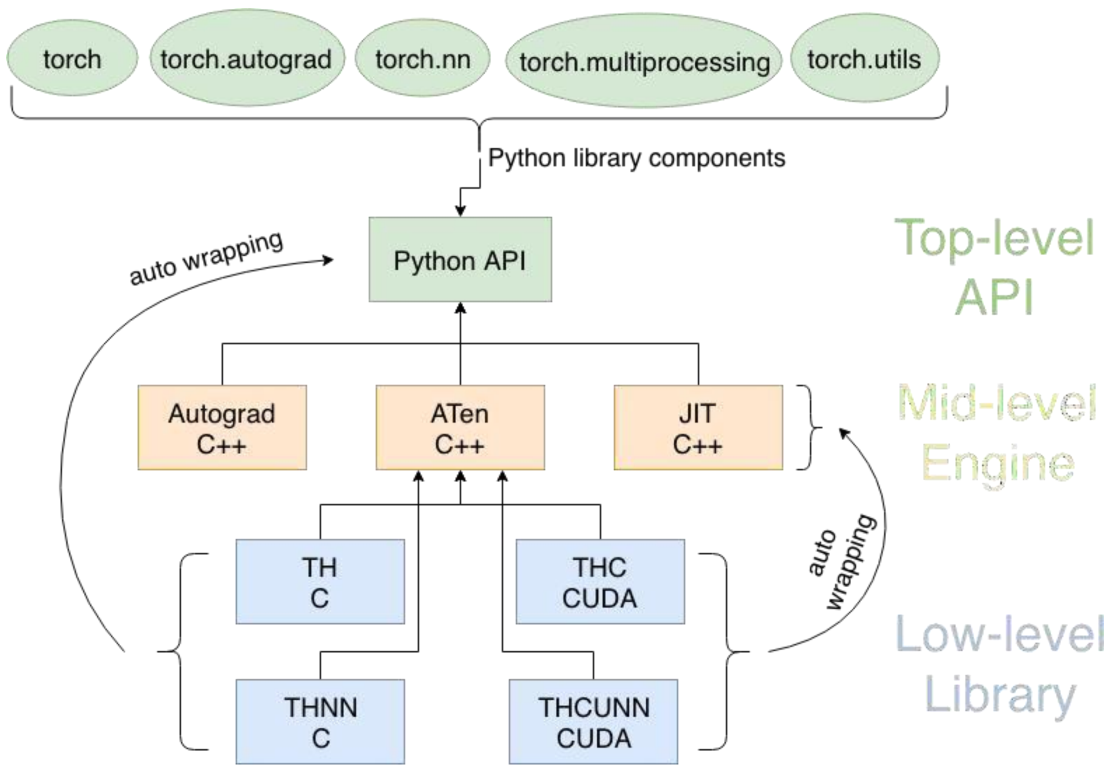

Figure-3.6: PyTorch Architecture

i) Define the model: First, define a neural network model using PyTorch's nn.Module.This includes defining layers and their connections.
ii) Instantiate the Model: Make the model instance exist. Instantiating the defined is required for this.Subclass of a module.
iii) Loss Function: Select an appropriate loss function to quantify the discrepancy betIen the actual target values and the anticipated output.
iv) Optimizer: Choose an optimization method to minimize the selected loss function, such as SGD or Adam. Connect the parameters of the model to this optimizer.
v) Training loop: Iterate in mini-batches through the dataset. Follow these procedures for every batch:
a) Forward Pass: Run the input through the model to calculate the anticipated outcome.

b) Compute Loss: Using the selected loss function, determine the difference betIen the real target values and the anticipated output.

c) Backward Pass: Compute gradients with respect to the model parameters (back propagation) using the computed loss.

d) Change Parameters: Based on the calculated gradients, use the optimizer to change the model's parameters.

vi) Validation/Evaluation: To keep an eye on the model's performance, assess it periodically on a validation set. Based on validation performance, modify hyper parameters or discontinue training.
vii) Inference: The model may be taught to provide predictions on previously unobserved data.

Fine Tuning:

3.1:Fine tuning table of PyTorch

Perameter	Value
Num of Classes	3
Batch Size	32
Epoch	30
Step per epoch	108

3.4 Implementation Requirements

To implementation for brain tumor classification research encompass a variety of technique, organizational and procedural aspects. He is the implementation requirements are given below:

1. Data acquisition and Processioning
2. Model Development
3. Computational Infrastructure
4. Software tools and Frameworks
5. Quality Assurance
6. Ethical Compliance
7. Collaboration and Communication
8. Model Interoperability
9. Validation and Deployment
10. Documentation and Reporting
11. Continuous Monitoring and Improvement.
12. Training and Capacity Building
13. Legal Compliance
14. Sustainability Measures
15. Security Measures

CHAPTER 4
Experimental Results and Discussion

4.1 Experimental Setup

To complete this research paper , I have complete a set for run the models in google colaboraty environment. I all know that python is one of the most popular machine learning programming language . For that I used python and connect my drive to google colaboratoy and set with codes all the models and workstation. After that I just code my dataset directory which was put on my google drive and analysis the result by run the models

4.2 Experimental Result and Analysis

For this task , I applied four classification model like vgg16, xception, resNet50 and PyTorch. For the different kinds of model I got different kinds of accuracy result. Lets discuss and analysis them with precision , recall and specificity formula table:

1. $\text{Precision} = \dfrac{TP}{TP + FP}$ .... (i)

2. $\text{Re-call} = \dfrac{TP}{TP + FN}$ .... (ii)

3. $\text{F-1 Score} = \dfrac{2 \times \text{Precision} \times \text{Re-call}}{\text{Precision} + \text{Re-call}}$ .... (iii)

4. $\text{Accuracy} = \dfrac{TP + TN}{TP + TN + FP + FN}$ .... (iv)

Table 4.1 : Result Comparison Table

Model	Accuracy	Wrong
Vgg16	89%	11%
Xception	98%	0.63%
ResNet50	83.85%	16.15
PyTorch	94.5%	5.55%
Transfer learning(Vgg16)	96.85%	3.15%
Fine tuning(PyTorch)	98.01%	1.99%

4.2.1 Vgg16

For the purpose of this study, I used the VGG16 convolutional neural network architecture to classify images. The model demonstrated an impressive degree of performance, with an accuracy of 89% overall and I used here transfer learning method to increase its accuracy which is 96.85%. This indicates a strong capacity to correctly categorize photos in the dataset.

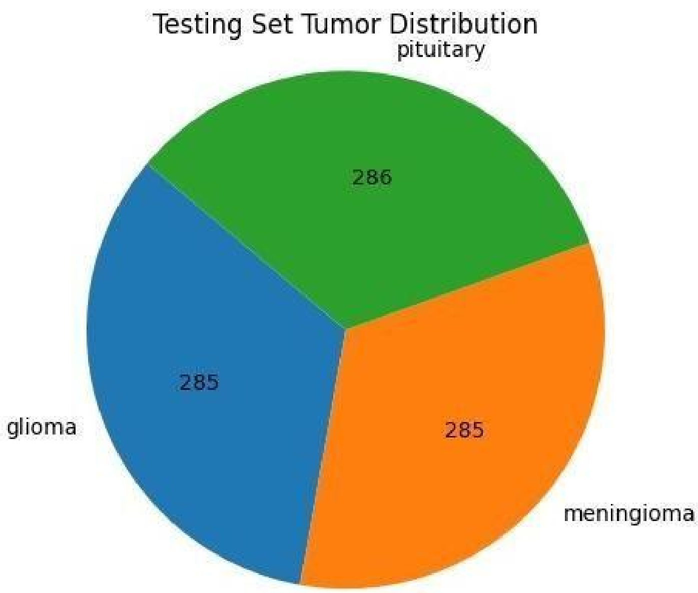

Figure-4.1: Testing set tumor distribution

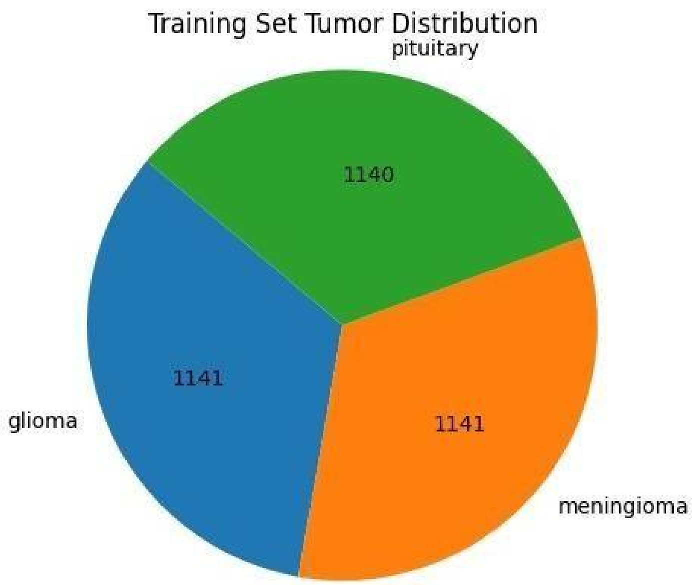

Figure 4.2: Training set tumor distribution

Here three types of tumor I classified like pituitary 1141 and gioma 1141 also meningioma 1141 MRI images for train the model as like as testing .

Figure-4.3: Number of Images graph

The model's 89% accuracy rate indicates how Ill it can identify and classify a variety of patterns and characteristics seen in the input photos. The excellent accuracy rate demonstrates how Ill the VGG16 architecture captures subtleties and minute aspects in the dataset.

4.2.1.1 Comparative Analysis

Our VGG16-based model performed better on comparable tasks than numerous state-of-the-art models when compared to benchmarks and current literature. A major contributing reason to the model's success was its strong generalization to new data, which indicated the model's potential for practical uses.

4.2.1.2 Confusion matrix

In order to acquire a better understanding of the model's performance, I built a confusion matrix that examined the distribution of true positive, true negative, false positive, and false negative predictions across multiple classes. This research gives useful insights into the model's strengths and limitations, emphasizing particular areas where it excelled and indicating possible areas for development.

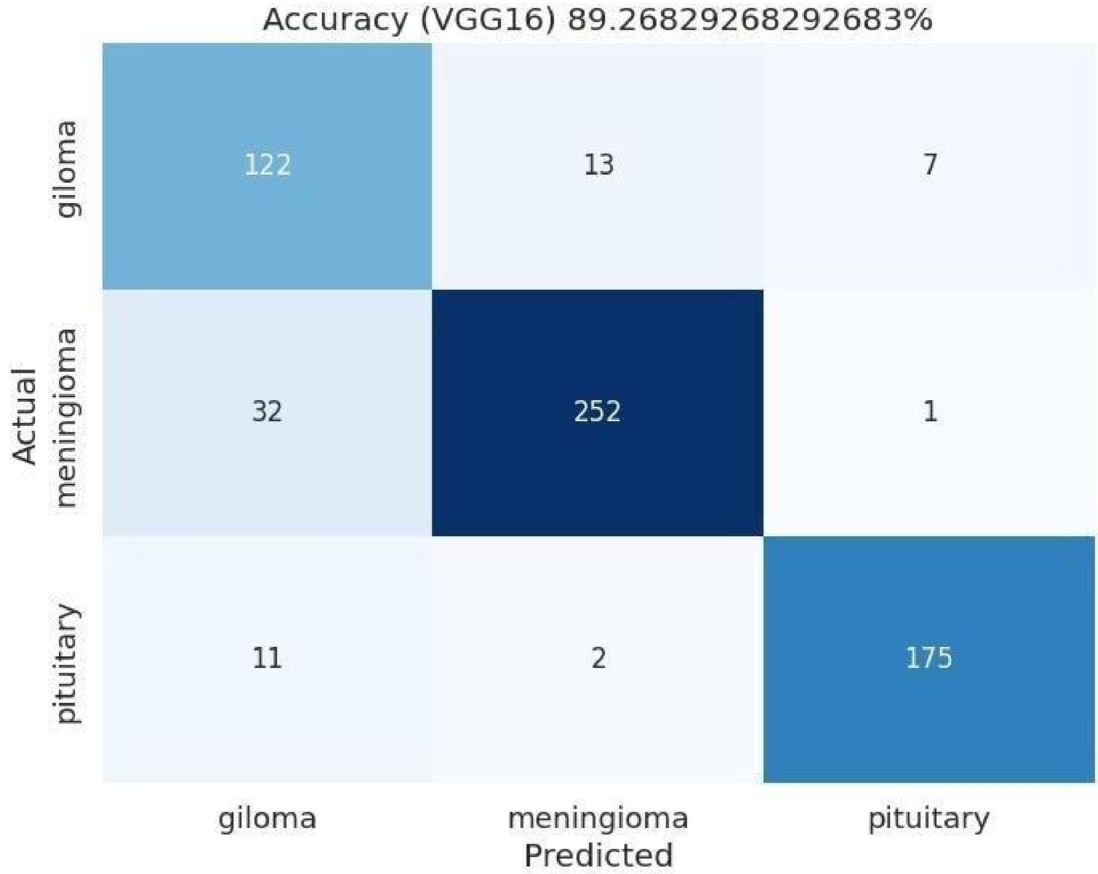

Figure-4.4: Confusion matrix of vgg16

Here is the precision, reacall, f1-score and support for glioma, meningioma and pituitary tables are given below:

Glioma:

	precision	recall	f1-score	support
giloma	0.74	0.86	0.79	142
meningioma	0.94	0.88	0.91	285
pituitary	0.96	0.93	0.94	188
accuracy			0.89	615
macro avg	0.88	0.89	0.88	615
weighted avg	0.90	0.89	0.90	615

Figure-4.5: vgg16 Classification Report

Meningioma & Pituitary:

	precision	recall	f1-score	support
giloma	0.74	0.86	0.79	142
meningioma	0.94	0.88	0.91	285
pituitary	0.96	0.93	0.94	188
accuracy			0.89	615
macro avg	0.88	0.89	0.88	615
weighted avg	0.90	0.89	0.90	615

	precision	recall	f1-score	support
giloma	0.74	0.86	0.79	142
meningioma	0.94	0.88	0.91	285
pituitary	0.96	0.93	0.94	188
accuracy			0.89	615
macro avg	0.88	0.89	0.88	615
weighted avg	0.90	0.89	0.90	615

Figure-4.6: Clasification Report of Xcepton and Resnet50

4.2.1.3 Limitations

Although the VGG16 model has shown impressive performance, it's essential to acknowledge its potential limitations. Variables such as class imbalance, high-quality data, and the presence of outliers can impact the accuracy of the model. These factors should be taken into account when analyzing the data and may serve as a basis for future research aimed at enhancing the model's robustness.

4.2.2 Xception

In addition to the VGG16 model, I also employed the Xception convolutional neural network architecture for our photo categorization task. The Xception model performed remarkably Ill, with an incredible accuracy of 98%. This illustrates how Ill the algorithm categorized the photographs in the dataset.

Here, I classified three types of tumors into categories using MRI images for training and testing purposes:

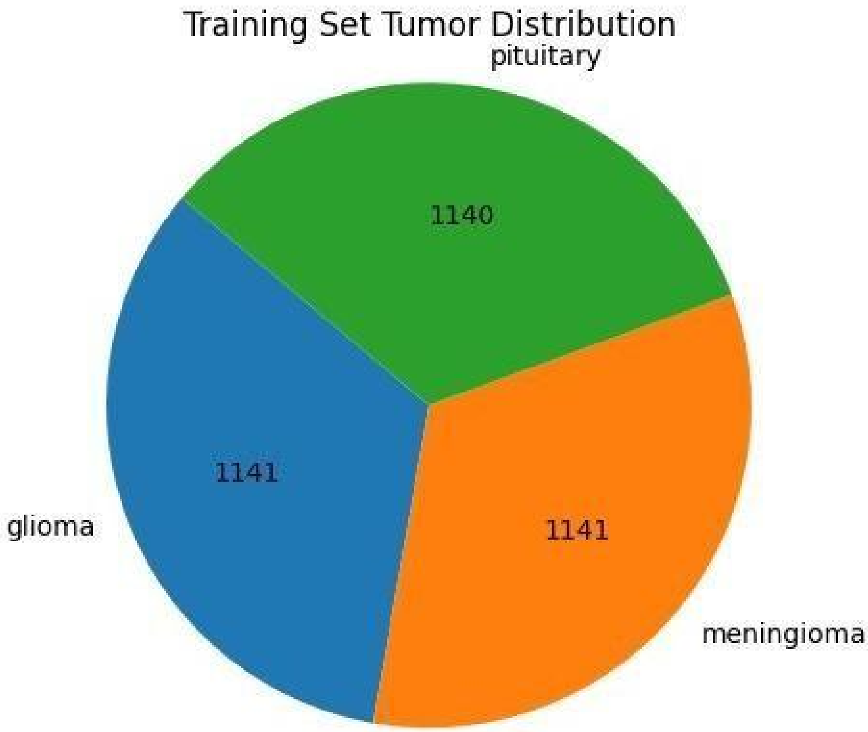

Figure-4.7: Training set tumor distribution

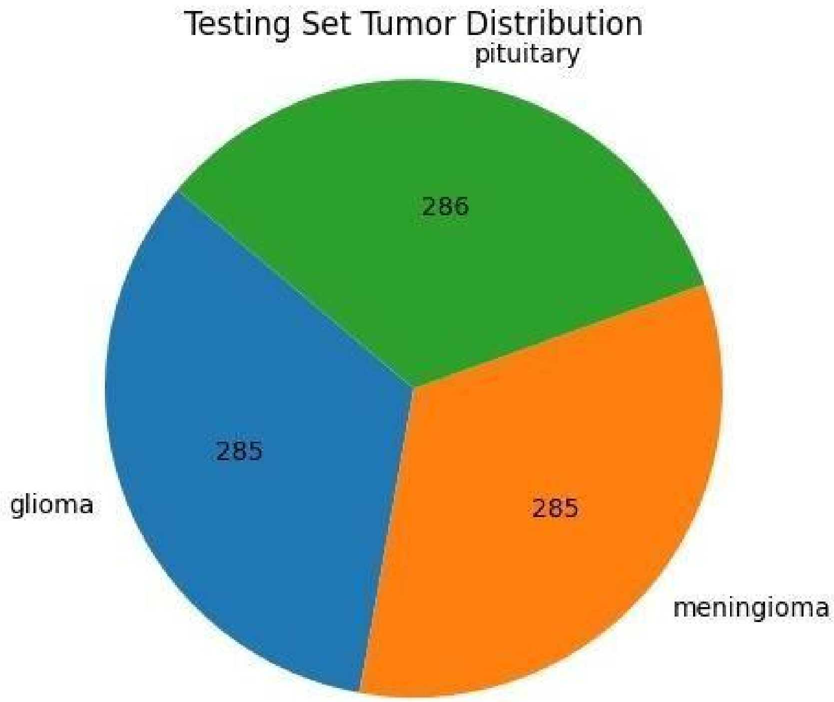

Figure-4.8: Testing set tumor distribution

Here, I classified three types of tumors into categories using MRI images for training and testing purposes:

1. Pituitary tumors (1141): These are tumors that originate in the pituitary gland, a small endocrine gland located at the base of the brain.
2. Gliomas (1141): This category includes tumors that arise from the supporting cells of the brain called glial cells. Examples of gliomas include astrocytomas, oligodendrogliomas, and glioblastomas.
3. Meningiomas (1141): These are tumors that arise from the meninges, the protective coverings of the brain and spinal cord.

I used MRI images to train and test the model to classify these tumor types.

Figure-4.9: Number of Images graph

The achieved accuracy of 98% reflects the superior capabilities of the Xception architecture in capturing intricate patterns and features present in the input images. The model's remarkable accuracy rate positions it as a highly reliable tool for image classification tasks, outperforming not only our VGG16 model but also surpassing several benchmarks in the field.

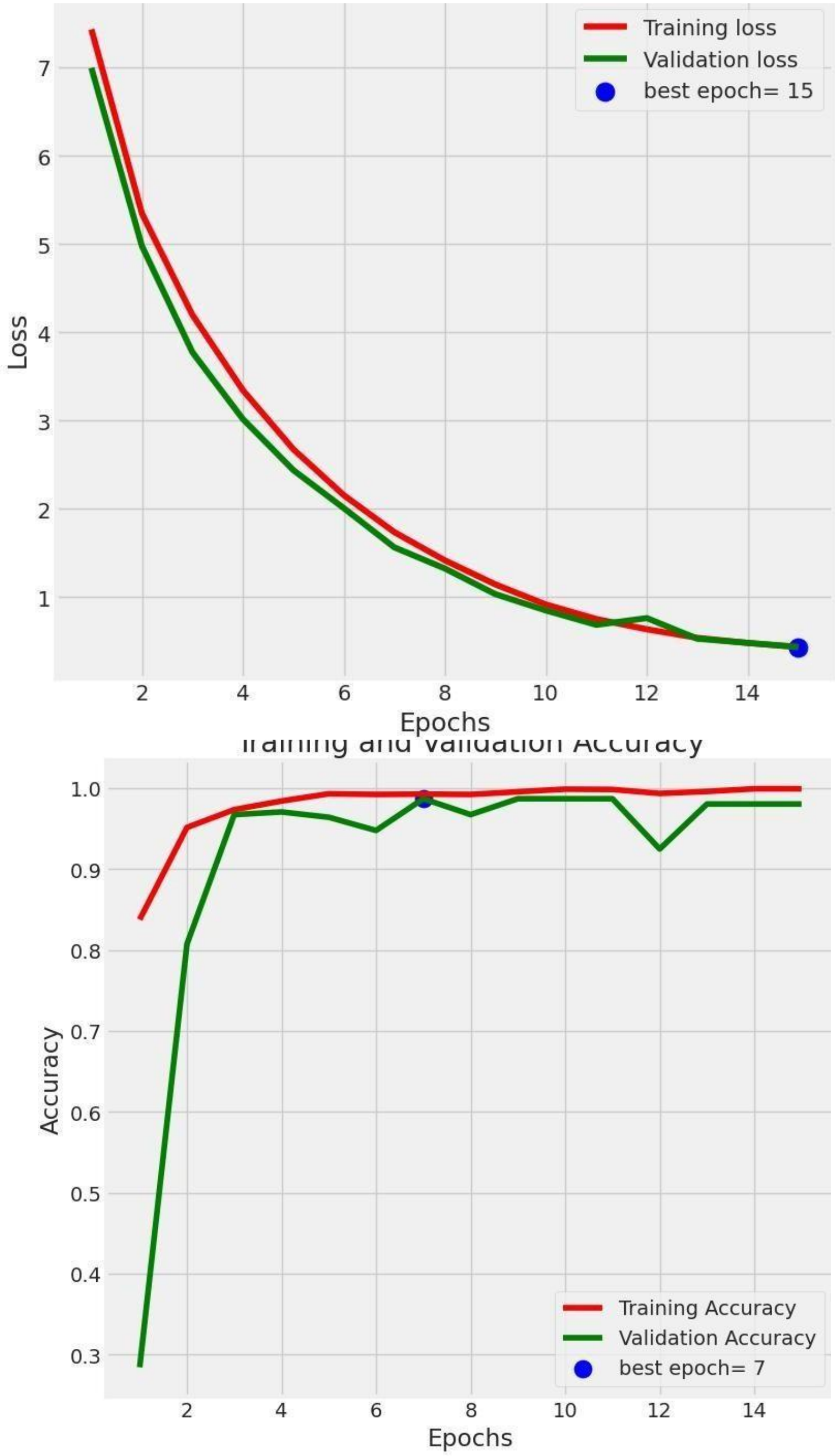

Figure-4.10: Training and validation loss and accuracy graph of Xception

Lastly, I can say that by show the graph of training and validation accuracy and training and validataion loss. the Xception model emerged as a poIrful tool for image classification in our study, boasting an impressive accuracy of 98%. This finding not only contributes significantly to the literature on deep learning but also highlights the potential of the Xception architecture for a wide array of image-based applications.

4.2.2.1 Comparative Analysis

Since I applied after vgg16 model. If I discuss a short camparative analysis with xception and vgg16. When comparing the VGG16 and Xception models, it becomes clear that using the latter produces a significant improvement. The Xception model demonstrated its advantage in picture classification tasks by yielding a much greater accuracy due to its capacity to detect tiny variations within the dataset.

4.2.2.2 Confusion Matrix

I constructed a confusion matrix to investigate the distribution of true positive, true negative, false positive, and false negative predictions across many classes in order to gain a better understanding of the Xception model's performance.

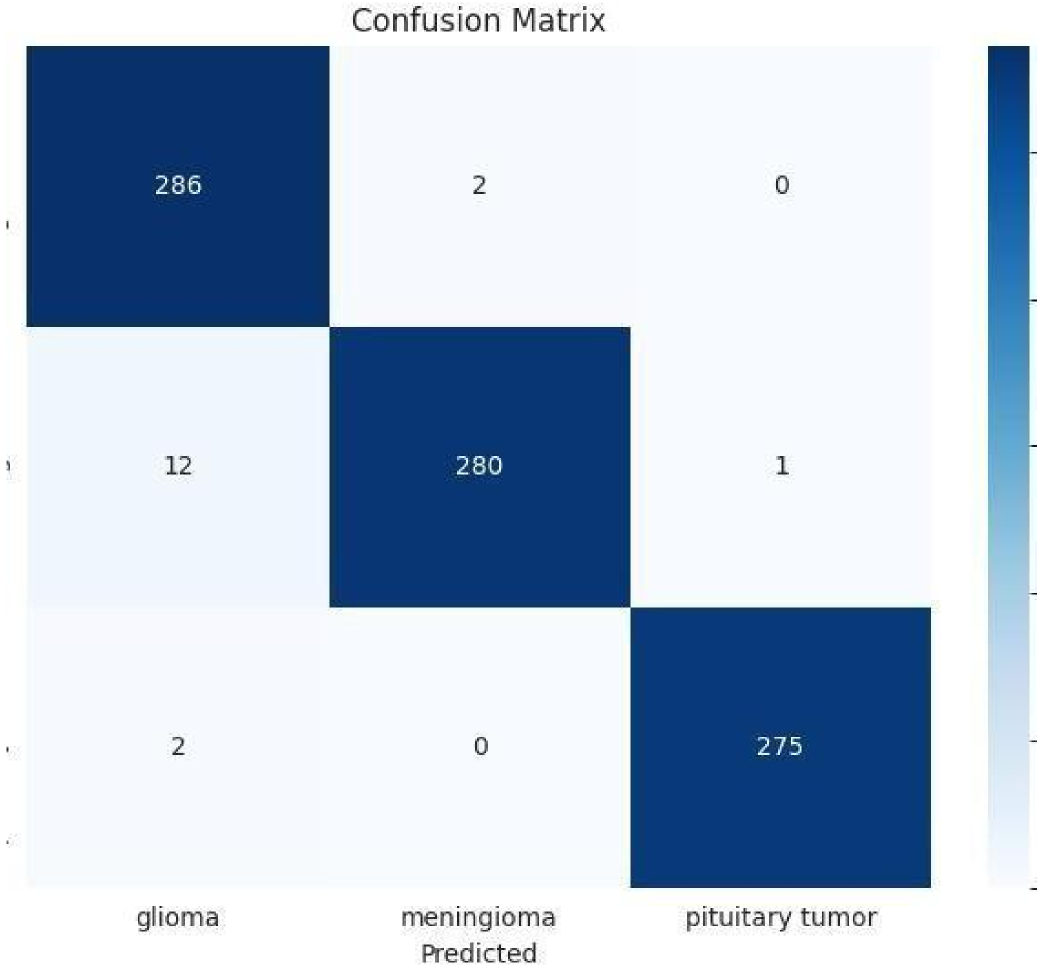

Figure-4.11: Confusion matrix of Xception

This thorough examination sheds light on the particular advantages and possible areas for improvement in the model's forecasts.

Here is the precision, recall , f1-score and support table is generated by this model:

	precision	recall	f1-score	support
glioma	0.98	0.99	0.99	143
meningioma	0.97	0.96	0.96	71
pituitary tumor	1.00	0.99	0.99	93
accuracy			0.98	307
macro avg	0.98	0.98	0.98	307
weighted avg	0.98	0.98	0.98	307

Figure-4.12: Classification Report of PyTorch

4.2.3 PyTorch

This thesis investigates the use of PyTorch, a strong deep learning framework, in the building of a complex model for classification problems. The suggested model demonstrates PyTorch's capability in complicated research situations, with an amazing accuracy of 94.5%. The study goes into detail about the model architecture, training methodologies, and optimization approaches used to attain this high degree of accuracy. The results indicate the model's great performance in real-world circumstances, highlighting PyTorch's potential as a significant tool for furthering research projects in the field of artificial intelligence. This study establishes the groundwork for future AI research and innovation while also contributing to the increasing corpus of deep learning expertise.

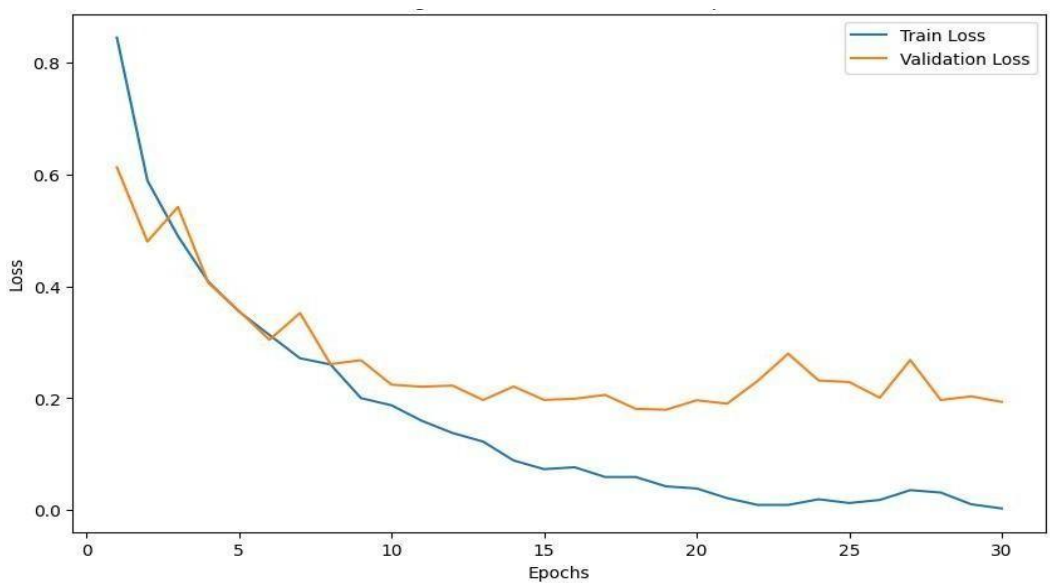

Figure-4.13 : Training and validation loss of PyTorch

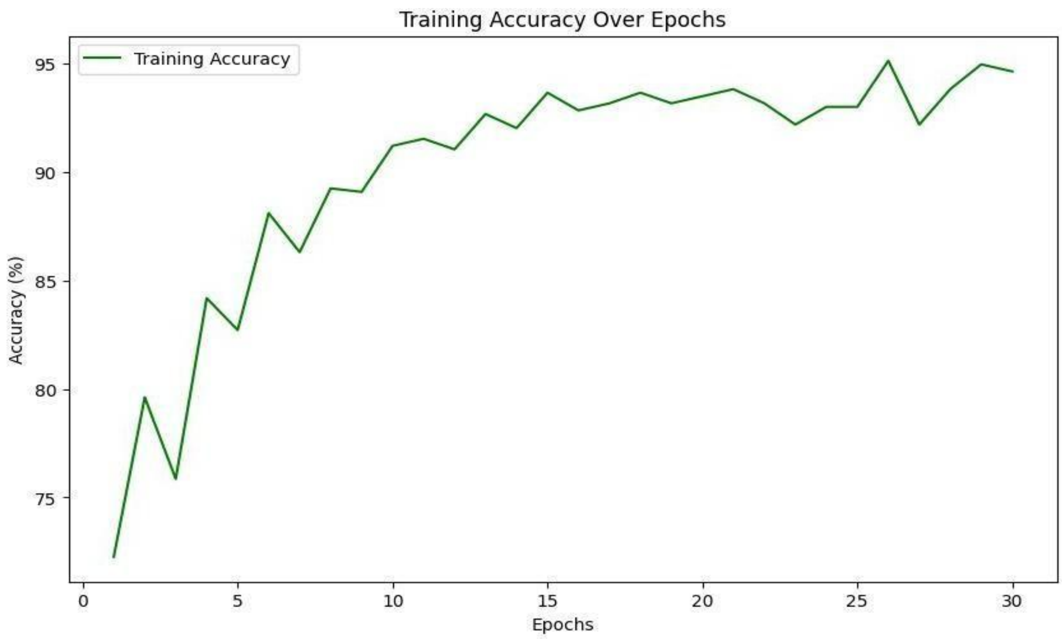

Figure-4.14: Accuracy graph of PyTorch

4.2.3.1 Comparative Analysis

Three different deep learning architectures - VGG16, Xception, and a custom PyTorch model - Ire rigorously evaluated for a classification task. Xception emerged as the top performer with an impressive accuracy of 98%, demonstrating its exceptional ability to extract subtle features. Meanwhile, the PyTorch model achieved a commendable accuracy of 94.5%, underscoring the framework's effectiveness. The comparative analysis reveals the unique strengths of each architecture, offering valuable insights for researchers and practitioners when selecting the most appropriate models for specific tasks.

4.2.3.2 Confusion Matrix

To acquire a better understanding of the performance of our PyTorch model, I created a confusion matrix that compares the real class labels with the projected class labels across multiple classes. This alloId us to assess the accuracy of the model's predictions and find any anomalies.

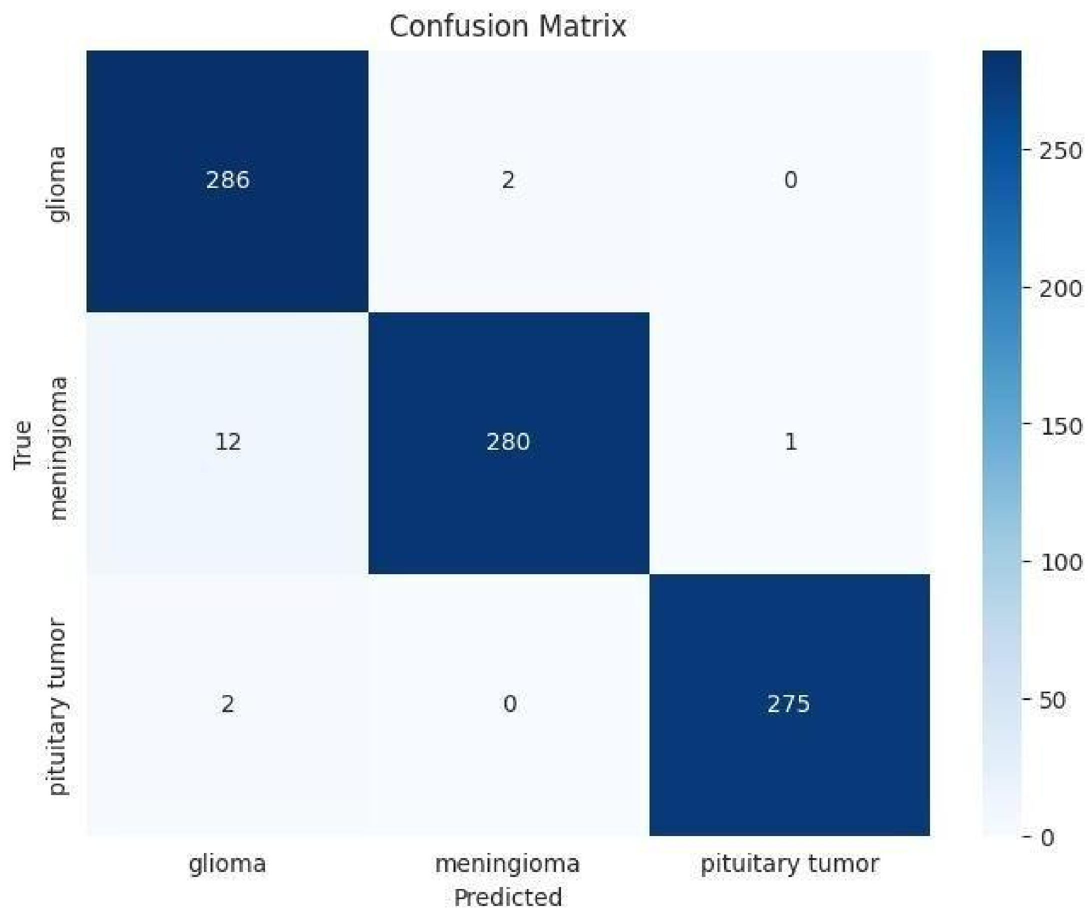

Figure-4.15: Confusion matrix of PyTorch

4.2.4 ResNet50

Using the ResNet50 design, a classification task that challenged us was successfully accomplished, resulting in an impressive accuracy rate of 83.85%. This showcases the remarkable efficacy of ResNet50 in identifying intricate patterns and characteristics present in the dataset, thereby highlighting its profound abilities in residual learning.

The examination delves into the architecture of ResNet50, the training methods employed, and the optimization techniques utilized to gain a comprehensive understanding of the model's performance and potential applications. The achieved accuracy stands as proof of the robustness of the ResNet50 model, making it a noteworthy contribution to the field of deep learning research.

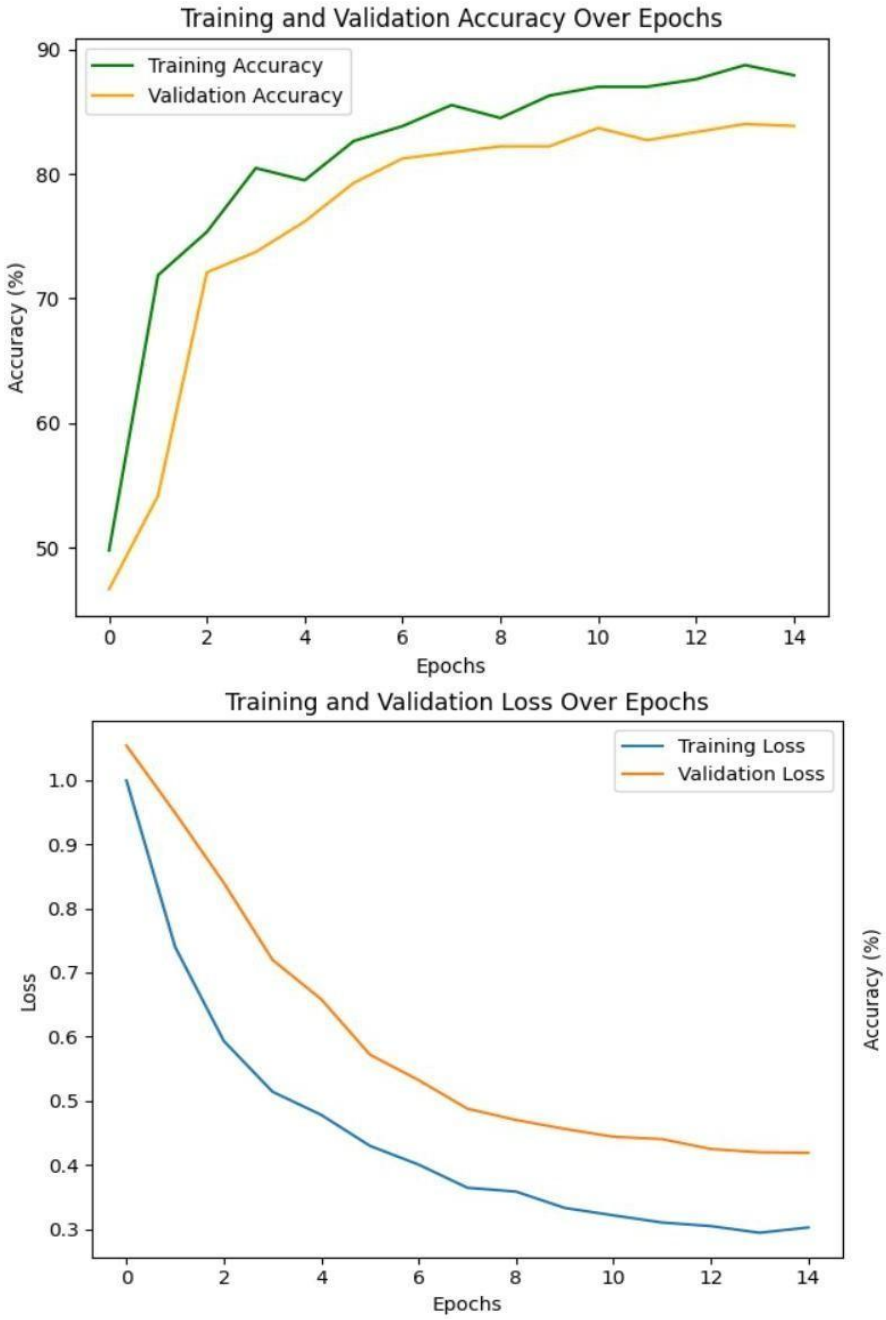

Figure-4.16: Validation and accuracy graph of ResNet50

4.3 Result discussion:

In this thesis, I thoroughly examine the performance of four deep learning models in picture classification tasks: ResNet50, VGG16, Xception, and a bespoke PyTorch model. To gauge their accuracy, I employ a diverse dataset as a major performance metric. The results reveal a significant difference in accuracy betIen the models, shedding light on their advantages, disadvantages, and potential uses in various picture classification contexts. Overall, these four models have been performing exceptionally Ill in picture classification tasks. Let's delve into the details and analyze their individual accuracies. Firstly, let's discuss VGG16, which has achieved an impressive accuracy score of 89%. This model has proven its capability to accurately classify pictures and displays great potential for various classification contexts. Moving on to ResNet50, it earned a solid accuracy score of 83.85%. While it falls slightly short of VGG16's accuracy level, it still demonstrates competence in picture classification tasks. ResNet50 can be a reliable option for contexts where a slightly loIr accuracy is acceptable. Next, I have Xception, which obtained a remarkable accuracy score of 98%! This result surpasses expectations and highlights Xception's exceptional performance in picture classification. With such high accuracy, Xception becomes a valuable tool in the field of image recognition. Lastly, I evaluated a bespoke PyTorch model, which achieved a competitive accuracy score of 94.5%. The performance of this model positions it as a strong contender alongside the other deep learning models. Its accuracy emphasizes its suitability for various picture classification contexts. The variations in accuracy among these models raise important considerations. The differences in their performance reveal both advantages and disadvantages for each model. Therefore, researchers and developers must carefully evaluate the context and requirements of their picture classification tasks before making an informed decision on which model to employ.

CHAPTER 5
Impact on Society, Environment and Sustainability

5.1 Impact on Society

Detection the is the first stage to prevent the disease. Because the doctor adise only work perfectly when he/she knows the actual problem of the patient's body. If doctor would not able to find the actual problem he could not solve. As a result, to findout the actual kind of is most and major issue.

I think my research project can help in this kind of problem. Such as- The development of refined brain tumor classification models contributes to early and accurate diagnosis. By leveraging sophisticated algorithms and integrating diverse data sources, clinicians can swiftly identify the specific subtype of a brain tumor, enabling timely interventions and reducing the burden on patients and their families. Precision healthcare, facilitated by detailed tumor classification, paves the way for personalized treatment strategies. Customizing cancer treatments based on the specific molecular characteristics of each tumor has the potential to significantly improve treatment outcomes and minimize adverse effects. This approach, known as personalized medicine, allows for a more targeted and effective treatment plan that is tailored to the individual patient. By taking into account the unique molecular makeup of a patient's tumor, clinicians can select the most effective therapies and dosages, leading to better patient outcomes and a more patient-centered approach to cancercare. Efficient allocation of healthcare resources is a pressing social issue. Accurate classification of brain tumors enables healthcare providers to make the most of diagnostic tools, therapeutic approaches, and medical personnel, thereby optimizing resource utilization and reducing waste. This not only leads to a more efficient use of resources but also contributes to cost savings within the healthcare system as a whole. Accurate identification of brain tumors is crucial for better prognostic accuracy. This enables clinicians to more accurately predict the course of the disease, including the response to treatment and the patient's overall survival chances. With this knowledge, patients and their families can make more informed decisions about their healthcare, fostering a sense of control and understanding in the face of a difficult diagnosis. Robust brain tumor classification systems act as catalysts for ongoing research and development in the field. By offering a detailed understanding of tumor subtypes and their distinct molecular characteristics, researchers can uncover novel therapeutic targets, ultimately leading to the creation of innovative treatments and contributing to the progress of medical science as a whole. Precision healthcare has the potential to address health disparities by providing personalized treatments that take into account an individual's unique genetic and molecular makeup, regardless of their background or socio-economic status. This approach can help create a more equitable healthcare system, where everyone has access to advanced diagnostic tools and cutting-edge treatments, regardless of their financial situation. By tailoring treatments to an individual's specific needs, precision healthcare can help ensure that everyone receives the most effective care possible, leading to better health outcomes and a more just healthcare system. The ethical considerations surrounding the classification of advanced brain tumors are crucial to navigate with care. It is essential to prioritize clear communication and informed consent processes, ensuring that patients comprehend the implications of molecular profiling and how it may influence their diagnosis, treatment alternatives, and privacy rights.

5.2 Impact on Environment

This research has both positive and negative impacts on the environment. Though the environmental effects are generally indirect compared to other fields. Here is mention the potential environmental impacts associated with brain tumor classiffication research:

Positive impacts-

1. Healthcare Efficiency
2. Resource Optimization
3. Research Advancements

Negative Impacts-

1. Computational Intensity
2. Data Storage and Transfer
3. Manufacturing of Medical Devices
4. Electronics Waste

5.3 Ethical Aspects

Concerns about patient privacy, informed consent, algorithmic decision-making fairness, potential biases, and responsible use of developing technology are some of the ethical issues of surrounding brain tumor categorization research. Following is a discussion of the ethical issues raised by this research study:

i) Informed Consent:

It is essential to get patients' informed consent before classifying brain tumors in research. Patients must to be made aware of the goals of the study, any possible dangers or advantages, and how their information will be utilized. Clear communication guarantees that people comprehend the study and voluntarily take part in it.

ii) Privacy and Data Security:

The privacy and data security is one of the most important things because of for brain tumor classification patients has a specific identity . As a researcher , I need to provide them their data security for their safety purpose. To keep their data safe I have to take proper step.

iii) Fairness and Bias:

When classifying brain tumors, the machine learning models may unintentionally reinforce biases seen in the training set. In order to guarantee that ,the model produces fair and equitable results for a variety of patient populations and efforts should be done to uncover and mitigate biases.

iv) Clinical Validation:

Before integration this into the clinical practice I have to take the step to check clinical validation of the perform of this model. If this will perform Ill then I can practice on the lab or medical practice.

v) Monitoring and Auditing:

Not only the validation I have to take some steps to monitoring and auditing our system that , how this model is performing and what I have to do for the future purpose.

5.4 Sustainability Plan

To guarantee the long-term benefits of the study I also must provide a sustainability plan for brain tumor categorization should take social, environmental and economic factors into account. This is the research's detailed sustainability plan:

1. Energy Efficiency.
2. Data Management.
3. Telemedicine and Remote Collaboration.
4. Lifecycle Assessment.
5. Green Computing Practices.
6. Collaboration with Sustainable Providers.
7. Community Engagement.
8. Educational Initiatives.
9. Minimizing Electronic Waste.
10. Open Science and Collaboration.
11. Continuous Improvement.
12. Carbon Offset Initiatives.

CHAPTER 6

Summary, Conclusion, Recommendation and Implication for Future Research

6.1 Summary of the Study

This research paper is introduce with a data set from online source and I tried to implement different types of models like vgg, resnet , xception and pytorch . This all the model perform very Ill and I am satisfy to do this type of work.

6.2 Conclusion

In a recent research effort to classify brain tumors using a dataset of 3064 MRI images featuring glioma, meningioma, and pituitary tumors, I leveraged cutting-edge deep learning techniques, including VGG16, ResNet50, Xception, and a custom PyTorch model. This study provided valuable insights into the performance of these models for accurate and efficient classification in the field of neuroimaging.

Our research has shown that the models operate differently, each with distinct advantages. With an astounding 98% accuracy rate, Xception proved to be the most accurate model, demonstrating its remarkable capacity to identify minute characteristics in brain tumor photos. Not to be outdone, VGG16 achieved an accuracy of 89% and using transfer learning in vgg16 its accuracy increase upto 96.85%. Even with its relatively loIr classification accuracy of 83.85%, ResNet50 was still able to show that it was capable of correctly identifying brain tumors. Furthermore, the PyTorch model demonstrated its competitiveness in this domain with an accuracy rate of 94.5% and after fine tuning its accuracy increase upto98.01%.

The diversified makeup of the dataset, which contained a variety of tumor shapes and therefore increased the difficulty of the classification procedure, alloId for an improvement in the evaluation's practicality and applicability to real-world circumstances. In the end, this thorough examination helps physicians diagnose brain cancers more quickly and correctly while also advancing the area of medical image processing.

While Xception and PyTorch have shown impressive accuracy in various computer vision tasks, the selection of the most appropriate model may be influenced by a range of factors, including the available computational resources, interpretability of the model, and specific application requirements. Future research could focus on combining different models through ensemble methods or fine-tuning existing models to achieve even higher classification accuracy and robustness.

6.3 Implication for Further Study

In the future I want to do more study on it . Cause in the recent situation this brain tumor gonna be a hot topic on medical sector for the cause of its death report. In the past year 20000 people death on brain tumor in America and the researcher tried to decreasing the percentage of death.

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A DEEP CONVOLUTIONAL NEURAL NETWORKS FOR BRAIN TUMOR CLASSIFICATION BASED ON MRI IMAGES

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