CA2 - A CASE-STUDY REPORT
On

Brain Tumour Detection using Transfer Learning

MASTER OF TECHNOLOGY
IN
Artificial Intelligence and Machine Learning

SUBMITTED BY

D Vamsidhar
(PRN - 24070149005)
Parth Desai
(PRN - 24070149017)
Sagar Joshi
(PRN - 24070149010)

॥वसुधैव कुटुम्बकम्॥

SYMBIOSIS INSTITUTE OF TECHNOLOGY, PUNE – 412115

(A CONSTITUENT OF SYMBIOSIS INTERNATIONAL (DEEMED UNIVERSITY))

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1. INTRODUCTION

1.1 Background

Brain tumours, a significant concern for all professionals and care seekers in the field of healthcare due to its severe effects on both mental and physical health of the victims and on mortality too. Magnetic Resonance Imaging (MRI) is the biggest revolutionizing invention which has improved the quality of diagnosis of various health conditions and helped both doctors and patients irrespective of their economic background [1]. MRI produces high resolution images of internal organs of the human body like brain, pancreas, kidneys etc. Similarly, MRI helps in detecting brain tumours that form due to uncontrolled growth of brain cells which leads in the absorption of nutrients meant for healthy cells thus resulting in failure of other cells due to lack of nutrition.

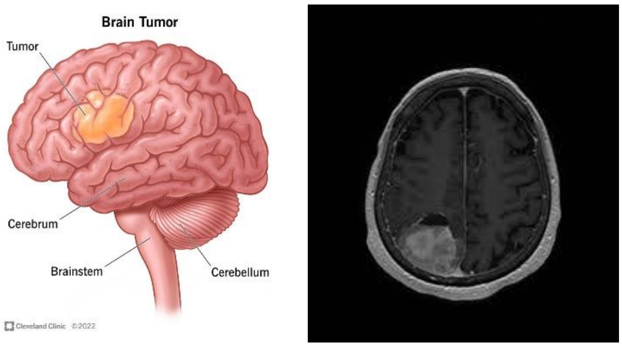


Figure 1. Structure of Brain with tumor and MRI of Brain with tumor

Studies show that there are 7 to 11 cases of brain tumor for every 100,000 in various age groups per year. There are many surveys and research which prove that number of victims of brain tumor is increasing rapidly. There are studies that claim that 227,000 people die out of this illness every year. An early diagnosis of a brain tumor may help prevent disability [2]. Using AI in healthcare had lot of positive impacts. One of those positive impacts is application of deep learning pre-trained models for brain tumor detection [3].

1.2 Motivation

The main motivation behind working on brain tumor detection is to build a model that accurately detects the tumor in the brain which helps in diagnosing and understanding patient's condition and help to analyze the process of treatment. Since the detection of tumor requires human involvement in general and may lead to potential human errors which is dangerous. So, to avoid such consequences, this will be the most helpful solution. Brain tumour is one of the most dangerous health disorders that a human body can manifest. It is typically classified into two types which are primary and secondary. A primary brain tumour forms in the brain itself and stays there, whereas a secondary brain tumour starts in a different part of the body and spreads to the brain [4].

2. LITERATURE REVIEW

2.1 Systematic Literature Review/Bibliometric Review

a. Machine Learning Techniques

Various healthcare applications such as patient risk stratification, personalized medicine recommendations, electronic health records (EHR) data analytics. When it comes to brain tumour detection techniques and algorithms like RF, SVM, AdaBoost1 and RUSBoost to localize the brain tumour in the MRI Images [5].

The machine learning techniques use algorithms like SVM, random forest classifier and decision trees where the training data has brain MRI images and the segmented brain tumour for that image. For better results, the SVM algorithm was also modified like Proximal SVM and twin SVM. Proximal SVM is a simpler classification algorithm which considers all data points in the dataset instead of identifying support vectors and plotting the hyperplane and creates a boundary close to each class instead of increasing the margin of the margin. Twin SVM looks for two boundaries or hyperplanes, one hyperplane that is near to class1 and far from class 2 and second hyperplane that is near to class 2 and far from class 1 [6].

b. Deep Learning Techniques

We have many deep learning models used in various fields like finance, healthcare, technology, agriculture etc. but healthcare industry needs most solutions to complex problems like clinical image analysis, handling electronic health records and genomics which employ complex models like DeepBind, CNNs, RNNs, Human Activity Recognition (HAR), LSTMs which also require hyperparameter tuning and adjustment of learning rates for better results according to dataset [7]. There are few challenges which employing deep learning models to solve the above problems which are volume of data, quality of data, progression of a disease, domain complexity and interpretability of deep learning models [8]. Another type of challenge faced heavily in the field of healthcare is increasing types of data which are electronic health records, genomic records, image dataset, X-Ray and MRI images increases the complexity of the code due to increased requirement of preprocessing and storage of data [8].

Existing projects that have produced high accuracy outputs use deep learning models like Gaussian Convolutional Neural Network (GCNN) on two datasets. These models produced an accuracy of 99.8% and 97.14% of accuracy on the two datasets. For image preprocessing the following methods like image cropping, rotating, flipping, inducing noise and transforming the colour space have been used[9].

c. Preprocessing Techniques

To have best predictions with high accuracy, precision and ideal recall values and f1 scores, it is necessary to preprocess the image dataset to capture maximum features from the images which will lead to better predictions and accuracy [10]. Techniques like Intensity normalization, discrete wavelets-based decomposition, augmentation, ultra-light deep learning architecture-based feature extraction which creates a large impact on model performance because this helps the model to capture as many details as possible [11]. Convolutional Neural Network was found to be better at executing the above techniques with application of L2 Regularization for improved generalization. To evaluate the performance of UL-BTD (Ultra-Light – Brain Tumour Detection) framework machine learning models like SVM, KNN and RF were employed [5].

To capture the details in a Brain MRI image for maximum output it is necessary to extract texture features from the images using methods like Gray-Level Co-occurrence Matrix (GLCM) [12]. The texture extraction can be done using multiple other techniques like Scale Invariant Feature Transform (SIFT), Saliency Detection[13].

Scale-Invariant Feature Transform (SIFT) is an image descriptor that has been proved to be highly useful for image matching and recognition as captures lots of features from an image which is in grayscale [14]. One major drawback of this technique found during the experimentation of this project due to which this technique cannot be used is its high computational expense which is caused due to capturing of too many features from a brain MRI image[15]. Figure 2. shows the application of SIFT technique for MRI images of brain.

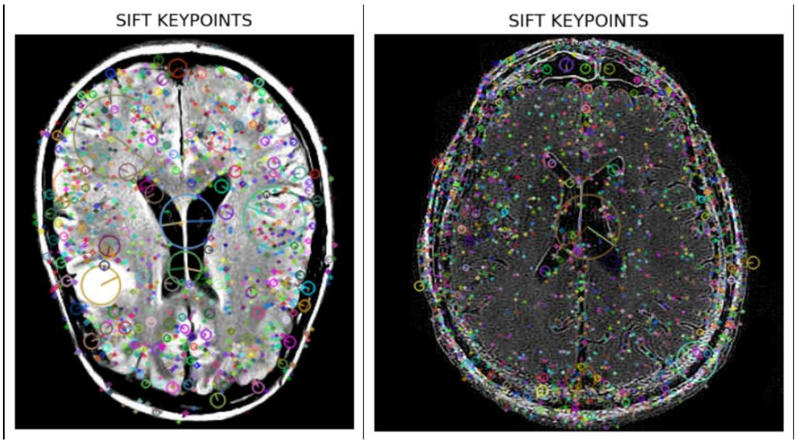


Figure 2. SIFT Features from Brain MRI Images

2.2 Review of methods available in the literature

Table 1. Comparison of methods available in the literature

S No.	Title of Paper	Methods/models	Limitations	Dataset used
1	Brain Tumor Detection and Classification Using Deep Learning and Sine-Cosine Fitness Grey Wolf Optimization [4]	CNN, Inception V3	1. High Computational Cost 2. Optimization challenges	BraTS' 20 Dataset
2	Intelligent Ultra-Light Deep Learning Model for Multi-Class Brain Tumor Detection [5]	GLCM Exclusive Analysis, UL-DLA (Ultra-Light Deep Learning Architecture)	1. Black box nature 2. Resource limitations	CE-MRI Dataset
3	Machine learning and deep learning for brain tumor MRI image segmentation[6]	SVM, Proximal SVM, twin SVM	1. Variability in dataset 2. High computational cost	BraTS
4	Brain Tumor and Glioma Grade Classification Using Gaussian Convolutional Neural Network [9]	Gaussian CNN, Data Augmentation	1. Complex tumor shapes 2. Difficulty in interpretability	TCIA (The Cancer Imaging Archive) Dataset
5	Learning Texture Features from GLCM for Classification of Brain Tumor MRI Images using Random Forest Classifier [12]	GLCM (Gray Level Co-occurrence Matrix)	1. Sensitivity to image quality 2. Variability in image quality	Brain Tumour MRI Images
6	Brain Tumor Detection using Deep Learning[16]	Data Augmentation, YOLOv7	1. Black box nature of model 2. Risk of underfitting due to lack of sufficient amount of data	Kaggle Brain Tumor MRI Dataset
7	Ensemble of Deep Learning Models for Brain Tumor Detection [17]	Ensemble Deep Convolutional Neural Network, VGG16	1. Resource limitations 2. Difficult to understand the model	3064 Brain MRI Images

8	Brain Tumor Detection and Classification on MRI images by a Deep Wavelet Auto-Encoder Model [18]	Seed Growing, Deep Wavelet Auto-Encoder Model	1. Storage limitations due to huge amount of dataset 2. Risk of overfitting	BraTS 2012, 2013, 2014, 2015 and ISLES
9	IoT Framework for Brain Tumor Detection based on Optimized Modified ResNet18[19]	SVM, Deep-CNN, ResNet18	1. Risk of improper training due to noisy images	Brain MRI Images
10	Improving Structural MRI Preprocessing with Hybrid Transformer GANs [20]	GANs, Skull Stripping, Intensity Normalization	1. Difficult to interpret the GAN model 2. Limited data images	Brain MRI Images
11	Brain Tumor Detection using Classification Using Transfer Learning [21]	Hybrid of VGG16-ResNet50	1. Resource limitations 2. Variability in dataset	Kaggle Brain MRI Images
12	Brain tumor detection using CNN, AlexNet & GoogLeNet ensembling learning approaches [22]	Pattern Classification, CNN, AlexNet, PCA, SVM	1. Imbalanced dataset 2. High Computational Cost	Brain Tumor Dataset

2.3 Summary of Literature Review/Research Gaps

The summary of the literature review done is, all the techniques mentioned above are computationally expensive methods which require high amount of data and building models like CNN with modifications which can make the interpretability of the model tough to understand which causes difficulty in hyperparameter tuning. Also, a few papers did not mention exact source of dataset which raises the question on quality of dataset. To overcome this problem, the best way is to leverage the full capacity of pre-trained models with highly effective image preprocessing techniques.

2.4 Problem Statement

Brain tumor detection remains one of the toughest jobs to be done in the field of healthcare, as it takes precise, least noisy MRI images to locate the tumor and treat it. Traditional diagnostic methods can be time consuming and have a high chance of lacking precise detection. Such errors lead to dangerous consequences. The proposed project aims to deal with these problems by developing a brain tumor detection system using modified pre-trained models which perform better by fine-tuning the hyperparameters.

3. METHODOLOGY

3.1 Block diagram

There are four phases to this project Preliminary Phases, Training Phase, Testing & Evaluation Phase, Web development and deployment phase.

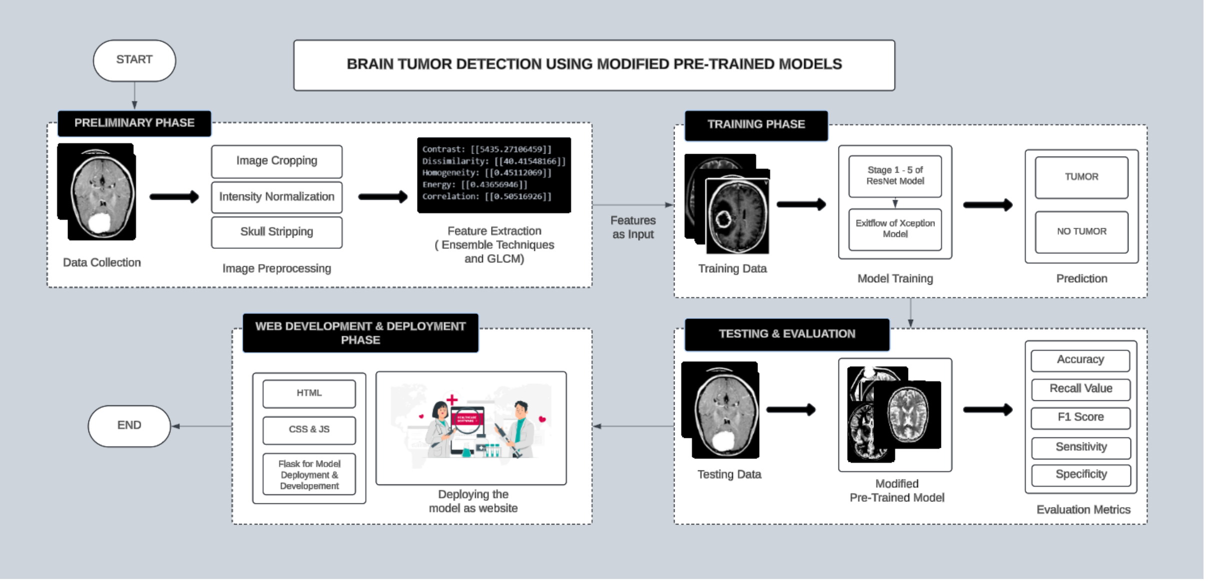


Figure 3. Block diagram of the method

3.2 Hardware/Software Requirements

Hardware Used

- **OS** – Windows 11
- **CPU** – AMD RYZEN 5 5600H; Clock speed – 3301 MHz
- **GPU1** – AMD Radeon TM Graphics, 144 Hz refresh rate
- **GPU2** – NVIDIA GeForce GTX 1650
- **RAM** – 16 GB RAM

Software/Tech stacks Used

- **Language** – Python
- **IDE** – VS Code
- **Technologies** – Deep Learning Pre-trained models

3.3 Method/Model Description

3.3.1 Image Preprocessing Techniques

The brain tumor images collected for this project were subjected to image preprocessing and feature extraction which is the preliminary phase of the project. The initial phase of this project consists of three important tasks which are data collection, image preprocessing and feature extraction.

Techniques such as Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), Gray-Level Co-occurrence Matrix (GLCM), Saliency Detection are known to be feature extraction techniques that are helpful to convert normal MRI images into processed images which shall later be used to extract features using machine learning techniques[23] [24].

Skull Stripping is one of the many techniques that was used as part of experimentation for searching suitable techniques for this project [25]. This technique helps in removing unnecessary non-brain tissues from the brain which might create disturbance while training the model. This is an important neuroimaging technique because it helps is isolating brain tissues [26]. In our experiment, it successfully isolated tumor areas from brain. Figure 3 and 4. Shows the results of our experimentation with skull stripping technique.

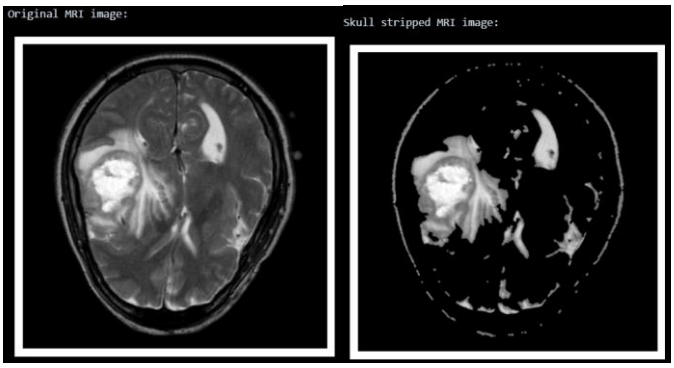


Figure 4. Skull Stripping technique applied on MRI image with Tumor

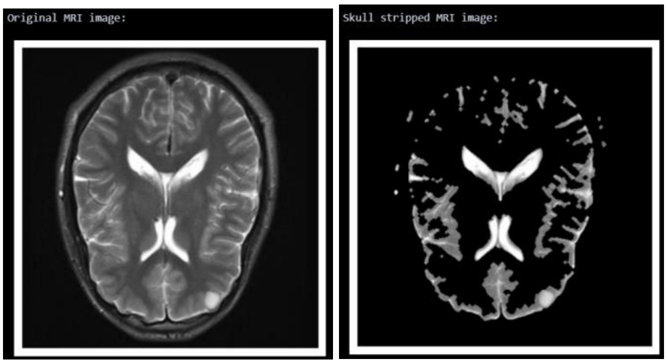


Figure 5. Skull Stripping technique applied on MRI image with No Tumor

3.3.2 Machine Learning Techniques

Currently multiple techniques are being experimented and reviewed which are most preferable in extracting features from the brain MRI images. Few of the techniques which have grabbed a lot of attention are ensemble machine learning techniques like Random Forest for Feature Extraction, Support Vector Machines and K-Nearest Neighbors [27][28].

For experimentation, the methods in use are machine learning techniques like Random Forest for Feature Extraction, SVM (Support Vector Machine), KNN (K-Nearest Neighbors) and Decision Trees, Auto-Encoders [29]. There are studies which uses four machine learning algorithms out of which two are parametric algorithm, ANN (Aritficial Neural Networks) and SVM (Support Vector Machines) and two non-parametric algorithms such as KNN (K Nearest Neighbours) and Decision Trees [30] [31].

First experiment is done using random forest algorithm. Algorithm of Random Forest for feature extraction is:

Algorithm RF:
Step 1: import necessary libraries numpy, cv2, RandomForestClassifier.
Step 2: load the MRI image.
Step 3: Preprocess the image through resizing and flattening.
Step 4: Create a dataset with X as two copies of flattened image and define corresponding binary labels = [0,1] where 0 means no tumor and 1 mean tumor.
Step 5: Split the data into training and testing data.
Step 6: Train RandomForest Classifier with n_estimators = 100.
Step 7: Extract feature importance using rf.feature_importances_ and print them.

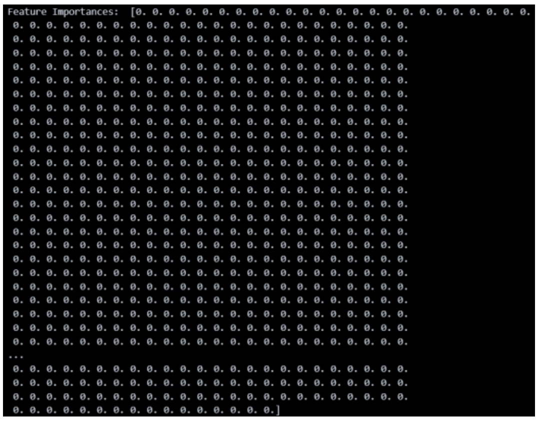


Figure 6. Result of Random Forest program for Feature Extraction

Further, the experimentations were conducted on GBM (Gradient Boosting Machine) for feature extraction which showed similar results to that of Random Forest algorithm[32].

Algorithm GBM:
Step 1: import necessary libraries numpy, cv2, GradientBoostingMachine.
Step 2: load the MRI image.
Step 3: Preprocess the image through resizing and flattening.
Step 4: Create a dataset with X as two copies of flattened image and define corresponding binary labels = [0,1,0,1] where 0 means no tumor and 1 means tumor.
Step 5: Split the data into training and testing data.
Step 6: Train RandomForest Classifier with n_estimators = 100.
Step 7: Extract feature importance using rf.feature_importances_ and print them.

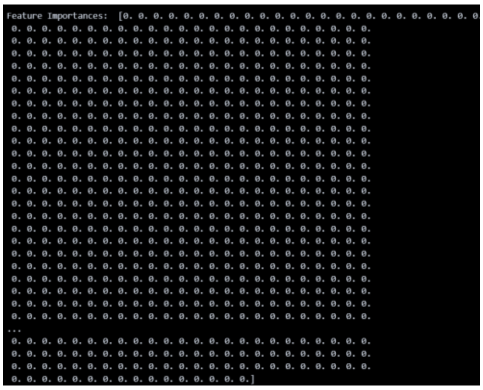


Figure 7. Results of Gradient Boosting Machine program for Feature Extraction

3.3.3 Deep Learning Techniques

For deep learning, it is found that leveraging and integrating multiple pre-trained models has been more beneficial in achieving higher accuracy, precision, recall values which implies that the overall performance can be improved [33]. To use the pre-trained models to their maximum potential, few improvements in data and few improvements in the pre-trained models by performing hyperparameter tuning like changing optimizer where values of Adam, SGD, RMSprop can be used and trained and tested on the images [34] [35].

ResNets are pre-trained models which deal with the challenge of training deep learning neural networks [36]. Traditional deep learning models suffer from problems like vanishing/exploding gradients which tamper the learning process of the model further leading to failure in model’s performance. Using pre-trained models such as ResNet helps in optimizing the models easily as hyperparameter tuning is easy in pre-trained models [37].

Similarly, another pre-trained model that produces accurate results is Xception model which is the improvised version of Inception model. Xception is a short form of Extreme Inception model. Xception model has a lot of layers in it which creates extreme depth in the architecture and the neural network which leads to effective training of model under fine-tuned hyperparameters [38].

As part of the experimentation, the ResNet50, ResNet101, ResNet152 and Xception models have been trained on the brain MRI images dataset. Based on the experiment results and analysis it has been found that ResNet101 and Xception models have performed better than others. Further inspection of the performance of other models like U-Net and MobileNet needs to be done so that a better architecture can be developed based on the results.

When experimenting with ResNet models with different hyperparameters, the performance of the model on testing data turned out effective for raw non-preprocessed images. It is expected to improve when the images are preprocessed, and the models are retrained. Out of all types of ResNets, ResNet101 had better performance on testing data.

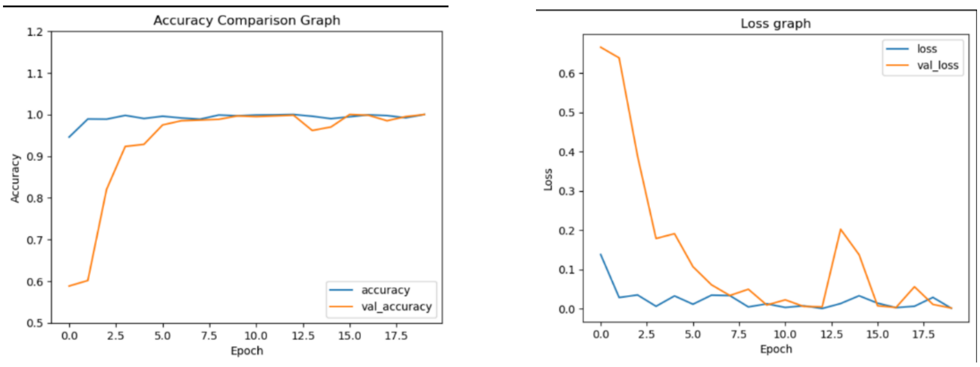


Figure 8. Performance Analysis of ResNet101

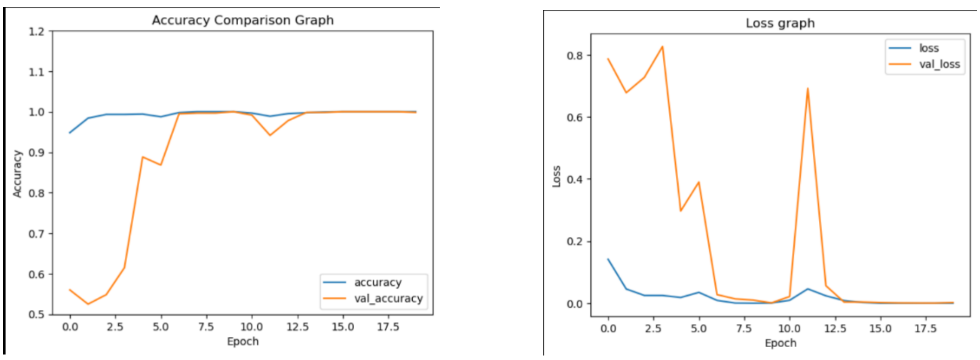


Figure 9. Performance Analysis of ResNet152

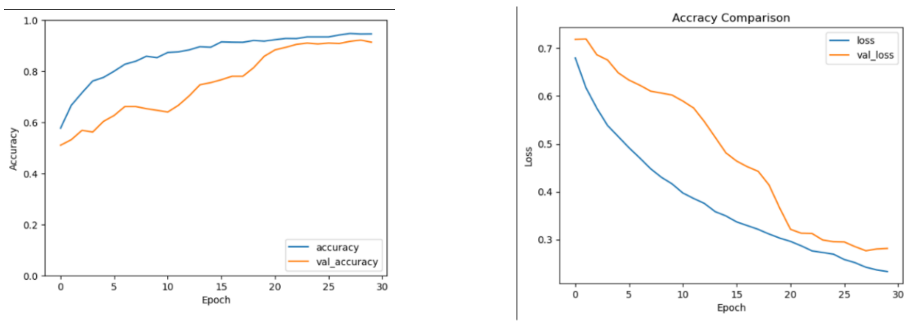


Figure 10. Performance Analysis of ResNet50 with SGD Optimizer

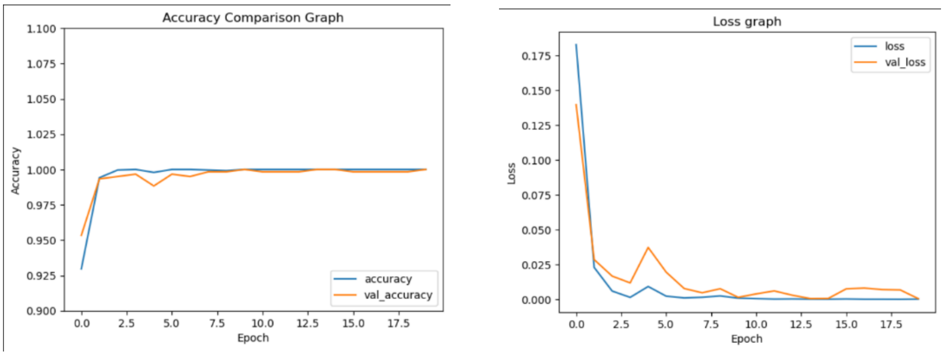


Figure 11. Performance Analysis of Xception Model

3.4 Datasets Description

We are using two separate datasets for this project to cover the maximum number of types of tumor from different angles.

One dataset is collected from Kaggle which is a collection of 3000 images in total which are divided and labeled into two classes called yes and no where each class has 1500 images in it which is perfectly balanced dataset. This balanced dataset is being used to train the model because of its clear least noisy images and most importantly evenly distributed into 2 classes. These images need basic preprocessing like cropping, resizing before proper technical preprocessing like intensity normalization.

The even distribution of the dataset has reduced a lot of work regarding data handling where we need to handle uneven distribution. Even distribution plays an important role in a deep learning project because improper distribution of data increases the chances of model becoming biased towards one class either Tumor or No Tumor [39] [40].

The following figures are sample images of the 1st image data collected from Kaggle.

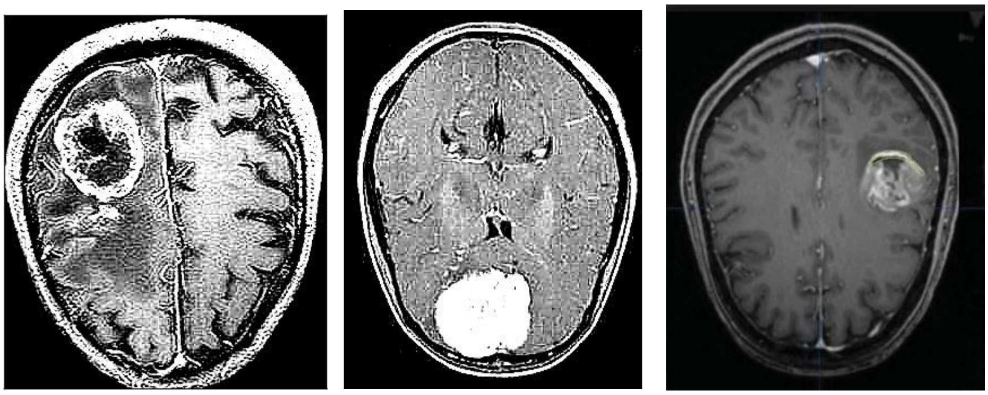


Figure 12. Brain MRI Images that have Tumor

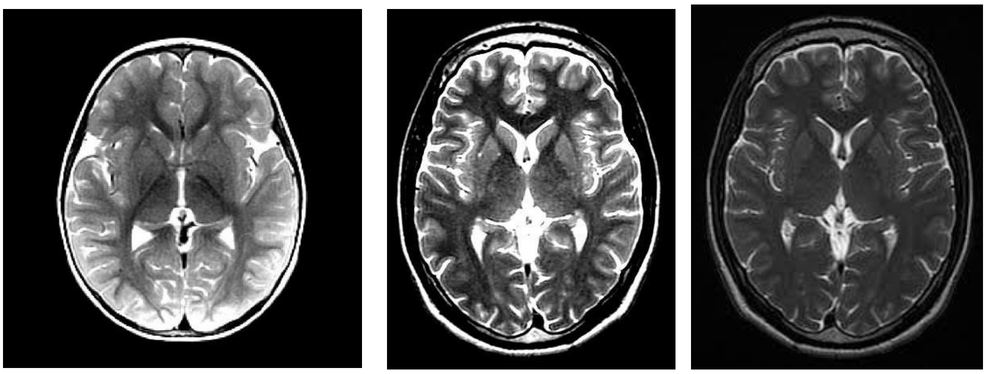
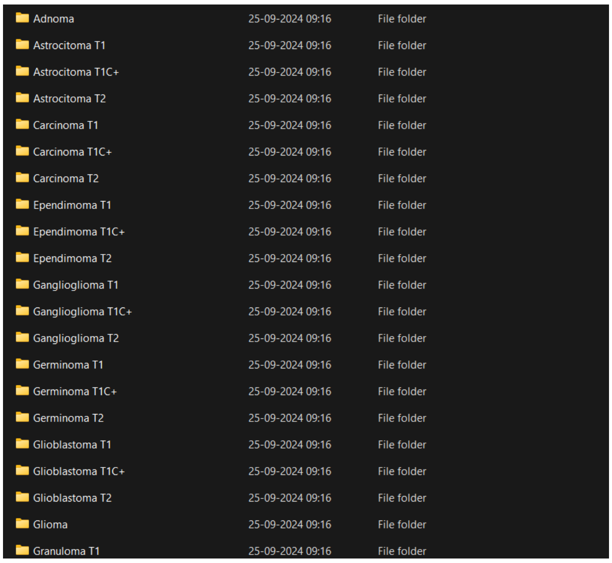


Figure 13. Brain MRI Images that do not have Tumor

The second dataset is also collected from Kaggle but this different from the first dataset as it has data with multiple classes like Adnoma, Glioma, Meningioma also with labelled separately based on T1, T2, T2+. These are the sample images of the dataset.



Adnoma	25-09-2024 09:16	File folder
Astrocitoma T1	25-09-2024 09:16	File folder
Astrocitoma T1C+	25-09-2024 09:16	File folder
Astrocitoma T2	25-09-2024 09:16	File folder
Carcinoma T1	25-09-2024 09:16	File folder
Carcinoma T1C+	25-09-2024 09:16	File folder
Carcinoma T2	25-09-2024 09:16	File folder
Ependimoma T1	25-09-2024 09:16	File folder
Ependimoma T1C+	25-09-2024 09:16	File folder
Ependimoma T2	25-09-2024 09:16	File folder
Ganglioglioma T1	25-09-2024 09:16	File folder
Ganglioglioma T1C+	25-09-2024 09:16	File folder
Ganglioglioma T2	25-09-2024 09:16	File folder
Germinoma T1	25-09-2024 09:16	File folder
Germinoma T1C+	25-09-2024 09:16	File folder
Germinoma T2	25-09-2024 09:16	File folder
Glioblastoma T1	25-09-2024 09:16	File folder
Glioblastoma T1C+	25-09-2024 09:16	File folder
Glioblastoma T2	25-09-2024 09:16	File folder
Glioma	25-09-2024 09:16	File folder
Granuloma T1	25-09-2024 09:16	File folder

Figure 14. Various classes of brain tumour

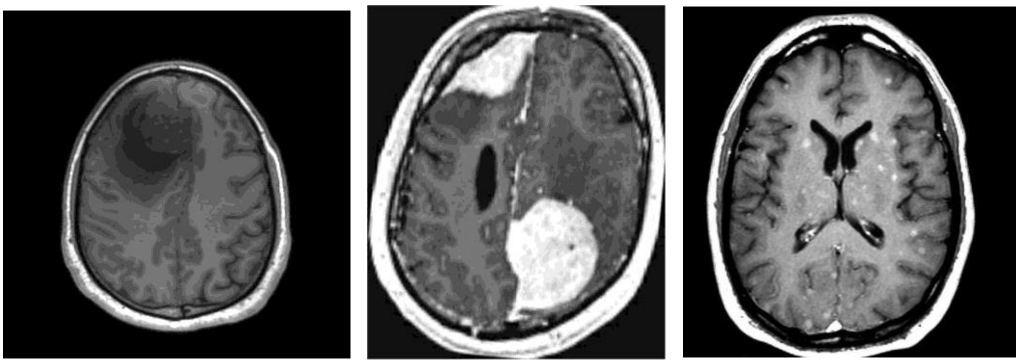


Figure 15. Astrocitoma T1, Adnoma and No Tumor respectively

4. LEARNING OUTCOMES AND FUTURE WORK PLAN

4.1 Learning Outcomes:

[1] This project helped to understand the importance of deep learning to solve problems like brain tumor detection.
[2] To complete this project lots of experimentation was done for every task like in the preliminary phase for feature extraction multiple techniques like Min-Max Normalization, Histogram Equalization, skull stripping.
[3] In the training phase, to determine which pre-trained model to use we had to learn about multiple models, their architecture and experiment with their performance through application of code.
[4] In the testing phase, we learned the performance of pre-trained models applied till now and researched on how to integrate two pre-trained models for better results.
[5] We will also learn the techniques to deploy the trained model as website using Python frameworks like Flask or Django.

4.2 Plan of Work

Task No.	Task Description	Duration	Status
1	Identification of project domain	26 Aug – 28 Aug 2024	Completed
2	Identification of project title	28 Aug – 30 Aug 2024	Completed
3	Searching the papers	31 Aug – 08 Sept 2024	Completed
4	Searching the datasets	09 Sept – 10 Sept 2024	Completed
5	Experimentation on pre-trained models with raw data	10 Sept – On going	In – process
6	Experimentation of feature extraction techniques	25 Sept – On going	In-process
7	Integrating finalized pre-trained models	08 Oct – 18 Oct 2024	Not yet started
8	Final Testing & Deployment	19 Oct – 31 Oct 2024	Not yet started
9	Research Paper Drafting	02 Sept – On going	In - process

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